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Organizational Changes and Older Workers' Training: Evidence from a Matched Employer-Employee Survey

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Organizational Changes and Older Workers' Training:

Evidence from a Matched Employer-Employee Survey.

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Abstract. In economies where labour forces are rapidly ageing, one policy-relevant question regarding technological and organisational innovations has to do with their labour-market consequences: do they affect the structure of employment and, as a consequence, do they hurt the employment prospects of older workers? This study discusses and tests a set of hypotheses concerning the impact of organizational changes on the observed relative disadvantage older workers face in training opportunities. For this purpose I use an Australian matched employer-employee survey, AWIRS-1995, which has been uniquely designed to capture those technological and organizational change recently experienced by many other OECD economies. Drawing upon previous work on measures of technological change at the industry level I am able to overcome the endogeneity problem detected in other studies. Finally, differently from the existing literature I distinguish between technological innovation and technological diffusion.

New and important findings of this study are that: (i) technological innovation may indeed cause some skill obsolescence among older workers; (ii) both the increasing extent of workplace restructuring and the intensification of technological diffusion, brought by the tightening of the input linkages between industries, contribute to explain a reduction in the relative disadvantage that older workers experience in terms of training opportunities observed in the last few decades (OECD, 1998). These findings suggest that there is ground for training and technology policies that reduce social exclusion, particularly in the face of substantially longer expected lives.

JEL classification codes: J24, J14, J28

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1 Introduction

Population aging is profoundly changing the composition of the labour force in OECD countries with widespread effects on public finances, fiscal policy sustainability and skill shortage. Recently, calls have emerged for policies that support labour market participation by older workers (OECD, 1998). However, the success of such policies relies on our understanding of the determinants of older workers' relatively narrow range of job opportunities available to older workers. One policy-relevant question regarding technological and organisational innovations has to do with their labour-market consequences: do they affect the structure of employment and, as a consequence, do they hurt the employment prospects of older workers?

The consequences of the widespread organizational changes adopted by firms in recent years are the focus of a number of very recent papers (Borghans and ter Weel, 2006; Aubert et al., 2006; Beckmann, 2004)). Evidence in the literature suggests that both technological and organisational innovations are biased against older workers. For instance, work re-organization tends to increasingly rely on multi-skilled workers (Borghans and ter Weel, 2006), but technological, particularly IT, changes and organizational restructuring tends to reduce hiring opportunities for older workers (Aubert et al., 2006). Beckmann (2004) uses a firm-level surveys for the period 1993-1995 to show that the adoption of both technological and organizational innovations within firms significantly contributes to shifting the age structure of the workforce against older workers.

In shaping senior workers' labour market opportunities, training is particularly important for senior workers, whose skills are likely to be substantially depreciated, (Bassanini, Booth et al., 2005). Despite its policy relevance the issue of whether technological and organizational change go hand in hand with increasing training opportunities for workers has been so far rather neglected. Two important stylized facts motivate this research. Firstly, older workers are at a relative disadvantage in terms of accessing formal types of training in the workplace (OECD, 1998). Secondly, recent evidence suggests that the extent of the size of the gap in training participation between older adults and younger adults, although still relatively large, has been declining over time.

Since the early 1970s, technological change has been a key factor in the reorganization of the firm (Bresnahan, Brynjolfsson and Hitt, 2002), the changes of its boundaries and the spread of alternative employment arrangements, such as outsourcing (Magnani, 2006). The literature on organisational change is recent, but several works, including Bresnahan et al., (2002), suggest that innovative workplace practices may induce depreciation of skill, what the literature often refers to as *skills obsolescence.* While most empirical studies have been primarily concerned with technical skills obsolescence, the process of skills depreciation due to changes in workers themselves (see e.g. McDowell, 1982), only few have been directly engaging with the link between workplace restructuring and economic skill obsolescence and the change in the way the workplace evaluates workers' human capital (de Grip, 2006). Despite the widespread sensation that technological and organizational changes increasingly require human skill to be successfully implemented, there still exists a profound gap in our understanding of the way firms' training decisions of older workers may be affected by the workplace reorganization.

Using AWIRS-1995, a uniquely designed matched employer-employee Australian survey, this paper discusses and tests a set of hypotheses concerning the observed relative disadvantage older (aged 45 and plus) workers face in training opportunities when firms face rapid technological change and workplace restructuring. The excellence of Australian labour market data has been recently acknowledged by leading labour economists (Freeman, 2006). As emphasised by Lynch et al., (1998), Australian surveys on training are uniquely suited to addressing empirical questions on the distribution and incidence of training among the various demographic groups and the factors that determine training decisions. The AWIRS, in particular is uniquely designed to capture those technological and organizational change that have been experienced by many other OECD economies. Compared to studies in the field cited above, this survey is able to more precisely capture the extend of organizational and technological change. Finally, this study uniquely contributes to the sparse literature on these issues by measuring technological change both at the workplace level and at the industry level and by distinguishing betweens two important dimensions of technological change, namely *innovation* and *diffusion*.

This study is organized as follows. In section two I draw upon Violante (2002) to sketch a model where technological change, both innovation and diffusion, differently impact upon skill obsolescence. Firms engage in the use of alternative employment arrangements (outsourcing). This framework allows me to derive a few empirical predictions of organizational and technological change on workers' training. In section three, after illustrating the nature of the Australian AWIRS 1995 and commenting on the construction of industry-level measures of technological change, I introduce the econometric specification. Section four discusses the empirical results. Section five concludes.

New and important findings of this study are that, contrary to a model prediction based on the assumption of substitutability between internal and external labour services, older individuals' training opportunities are not negatively affected by the spread of alternative employment arrangements. Furthermore, differently from other studies I am able to identify the specific role that technological innovation, as opposed to technological diffusion, plays in the process of skill obsolescence among older workers. Finally, this study shows that both the increasing extent of workplace restructuring and the intensification of technological diffusion brought by the tightening of the input linkages between industries, may contribute to explain a reduction in the relative disadvantage that older workers experience in terms of training opportunities observed in the last few decades (OECD, 1998).

2 Older workers and training: the impact of workplace organizational changes.

The striking changes occurring in the internal organization of the firm since the early 1970s are well known. According to Lindbeck and Snower (2001), increased functional flexibility and reduced task specialization *among workers* within a firm has gone hand in hand with increased specialization in production *among firms*, a down-sizing process that involves more narrow focus on a firm's "core competencies" in production and the outsourcing of "non-core competencies". Tasks that were previously performed by workers directly hired by the firm are now increasingly done under contract with firms in the business service sector and through employment arrangements that involve temporary workers, outsourcing and sub-contracting.

The causes of this phenomenon are still unclear but it is now commonly accepted that the pressure of the world economy has forced firms to focus on their distinctive resource profile - those competencies and capabilities that are unique, firm specific, valuable to costumers, non substitutable and difficult to imitate. The resulting emphasis on innovation, both technological and in terms of new resource combinations, has certainly contributed to wholesale changes in the internal organization of the firm. While it is well accepted that organisational developments such as reorganisations and changing management systems can have a dramatic influence on job content and may therefore increase the risk of skills obsolescence, less clear cut is the impact of these changes on workers' training opportunities. Older workers may be at relative disadvantage in using new technologies. The related empirical evidence however provides mixed results (see for example Borghans and ter Weel (2006) and Friedberg (2003)).

Economic theory does not provide a clear prediction on the sign of the relationship between technological change and training (Bartel and Sicherman, 1998). One argument is that innovation may be positive for older workers because they are more skilled and experienced.

On the other hand, innovation may negatively affect older workers if it accelerates skill obsolescence, that is, if it reduces the market value of their skills. Within this competing argument technological change makes training less likely. Furthermore, whether we think of internal and external (to the firm) labour services as substitutable or we think of outsourcing as a strategy that allows firms to focus on the activities in which they have a competitive advantage, organizational restructuring may well affect workers' training decisions.

Complex is also the evidence on the impact of firm restructuring on training. Interestingly, a number of studies find links between organizational changes and productivity growth. First, Siegel (1995) argues that the improvements in manufacturing productivity cannot be explained by measurement errors but rather by outsourcing, an increase in the rate of investment in computers, and unmeasured changes in the quality of output and the labor force. Similarly, ten Raa and Wolff (2001), relate the recovery of standard TFP growth in US manufacturing during the 1980s to an increased use of outsourcing of inputs from service industries as well as to technical change. To the extent that there exist a positive relationship between organizational changes and productivity, this can in fact expands all workers' training opportunities.

A rather central issue to assess the impact of organizational changes on workers' training opportunities is the relationship of complementarity or rather substitutability between internal labour services and those purchased by means of market mediated employment arrangements. Whether we think of internal and external (to the firm) labour services as substitutable or we think of outsourcing as a strategy that allows firms to focus on the activities in which they have a competitive advantage, organizational restructuring may well affect workers' training decisions. In the following section I propose a simple theoretical framework that will help us thinking about these issues.

2.1 The model.

The first aim of the model is to investigate how the pace of technological change, both in terms of innovation and diffusion, and organizational restructuring affects the training opportunities of older workers. I draw from Behaghel (2002) who solves from the optimal training profile along the career of a representative employee. In the second half of his/her career s/he faces three periods: period 1 (medium age worker), period 2 (older worker) and period 3 (old worker). Training affects productivity with a one period delay, so training occurring in period 1 is effective in period 2, while training occurring in period 2 is effective in period 3. As in Behaghel (2002) training decisions are born out of a "cooperative" game in the sense that training affects total surplus, which is then divided between employer and employee. This is consistent with the view often emphasized in the literature according to which there seems little doubt that the attitudes of older workers are a significant obstacle to their further participation in training. In this "cooperative" game training is chosen to maximize total surplus. As in Behaghel (2002) we do not assume any transition out of the employing firm before period three, when the firm is subject to a shock ϵ that affects workers' productivity in period 3 π_3. The shock ϵ has a uniform distribution in the range $[-k; k]$.

Technological change is formalized as in Violante (2002). A worker on a machine of age j, who next period moves on a machine of age j' can carry on the new job a fraction of the cumulated skills equal to $z_{jj'}$ determined by the transferability function $z_{jj'} = (1+\gamma)^{\tau[j'-(j+1)]}$. Thus the technological distance between machines of different vintages is filtered through a parameter τ.

In each period a firm adopts the newest technology (machines of age 0). Technology is innovated at the beginning of each period, so workers hired in period 1 and trained to use period-one latest technology will work with technology of age "zero" in period 2. Training endows workers with a skill z_{00} at the beginning of period 2. As in Violante (2002) $z_{00} = (1+\gamma)^{-\tau(a)}$ which implies that skills depend on the degree $\gamma, \gamma > 0$, of innovation from "new" machines of different generations and on the transferability of human capital τ between technologies of different age. Note that the degree of transferability of human capital between two subsequent generations of machine depends on a variable a for a worker's *age* at the time training takes place, with $\tau'(a) > 0$ This is a simple way to derive testable hypotheses on *(i)* the relevance of notions such as skill obsolescence in the face or technological change; (ii) the importance of age in relation to the hypothesis of skill obsolescence. In this respect note that for any given level of γ, the higher τ, $\tau > 0$ the less workers' skill is transferable across two subsequent vintages of machines. In other words τ is a measure of how specific (non-transferable) vintage-specific skill is. For any given level of the variable a, τ will capture the effect of technological diffusion in the sense that the less technology diffuses the more vintage-specific skill is.

In period 2 "older" workers receive training T_2, which endows them with skill z_{00} in period three. Training is costly according to the cost function $C(T_i) > 0$, with $C'(.) > 0, C''(.) > 0$ (increasing marginal costs to training). In period 3, the productivity of "old workers" π_3 is affected by the shock ϵ as follows:

$$\pi_3 = (z_{00})^2 T_1 + z_{00} T_2 + \epsilon \tag{1}$$

The surpluses derived from production and training in each period can be expressed as follows:

$$\begin{aligned} S_1 &= -C(T_1) - W_1 \\ S_2 &= z_{00} T_1 - W_2 - C(T_2) \\ S_3 &= \frac{1}{4k}[(z_{00})^2 T_1 + z_{00} T_2 + k - W_3]^2 \end{aligned} \tag{2}$$

where $W_i, i = 1, 2, 3$ are the wages paid to a worker in period i. Note that the surplus in period 3 is the product of the probability that the job is maintained in period 3, multiplied by the expected surplus in period 3, conditional on it being positive. We write the probability of maintaining a job in period 3 as $Prob(\pi_3 \geq W_3) = \Pr ob((z_{00})^2 T_1 + z_{00} T_2 + \epsilon \geq W_3) = \frac{k - W_3 + (z_{00})^2 T_1 + z_{00} T_2}{2k}$. Note that to guarantee that this probability is strictly between 0 and 1 we need to assume that k is sufficiently large.

Thus the firm's problem is to maximize total surplus derived from training older workers, that is

$$\max_{T_{i,i=1,2}} S = S_1 + \beta S_2 + \beta^2 S_3 \tag{3}$$

where β is a discount factor. The first order conditions are:

$$\partial S / \partial T_1 = \beta z_{00} - C'(T_1) + (\beta^2/4k)[(z_{00})^2 T_1 + z_{00} T_2 + k - W_3](2z_{00}^2) = 0 \tag{4}$$

$$\partial S / \partial T_2 = -\beta C'(T_2) + (\beta^2/4k)[(z_{00})^2 T_1 + z_{00} T_2 + k - W_3](2z_{00}) = 0 \tag{5}$$

From the f.o.c. we derive the following:

Proposition 1

The optimal levels of training in period one and period two, T_1^* and T_2^*, respectively, decreases as the rate of technological innovation, the technological distance between subsequent vintages of machines, increases.

Proof. From the f.o.c. (4), note that $C'(T_1) = \beta z_{00} + (\beta^2/2k)[(z_{00})^2 T_1 + z_{00} T_2 + k - W_3](z_{00}^2)$. A rise in γ does not affect the l.h.s of this equality, but it has two effects on the r.h.s. Firstly it reduces the coefficient of T_1. Secondly it reduces the term independent of T_1, namely $(\beta^2/2k)[(z_{00}T_2 + k - W_3](z_{00}^2)$. For this reason the optimal level of T_1 will drop. A similar argument proves the proposition for T_2^*. QED

Proposition 2

The optimal levels of training T_1^* and T_2^* increase as technology diffuses (τ drops) and workers' skill becomes less vintage specific.

Proof. From the f.o.c. (4), note that $C'(T_1) = \beta z_{00} + (\beta^2/2k)[(z_{00})^2 T_1 + z_{00} T_2 + k - W_3](z_{00}^2)$. A drop in τ does not affect the l.h.s of this equality, but it has two effects on the r.h.s. Firstly it increases the coefficient of T_1. Secondly it increases the term that is independent of T_1, namely $(\beta^2/2k)[(z_{00}T_2 + k - W_3](z_{00}^2)$. For this reason the optimal level of T_1 will increase. A similar argument prove the proposition for T_2^*. QED

It is relevant to notice that recent evidence suggests that the extent of the size of the gap in training participation between older and younger adults, although still relatively large in Australia, has been declining over time. The sources of this change, however are not immediately obvious. This simple model suggests that if the parameter τ changes over time and in particular it drops (for example due to rapid technological diffusion) the relative position of older workers in terms of access to training opportunities may change, although this simple model is clearly unable to predict unambiguously the direction of this change, given that both younger workers' and older workers' training would be affected by a change in τ. For this reason it is ultimately an empirical matter that I will discuss later on. This simply formalization capturing the effect of technological change on skill obsolescence allows us to reach another testable implication:

Proposition 3

For any level of the technological parameters γ and τ , age decreases the optimal levels of training. Furthermore the interaction of technological change (a rise in γ, or a rise in τ) and age has a negative impact on a worker's training. In other words:

$$\frac{\partial T_i^*}{\partial a} < 0; \qquad \frac{\partial T_i^*}{\partial \gamma \partial a} < 0; \qquad \frac{\partial T_i^*}{\partial \tau \partial a} < 0 \qquad i = 1, 2` \tag{6}$$

Proof. From the f.o.c. (4), note if age increases, the condition $C'(T_1) = \beta z_{00} + (\beta^2/2k)[(z_{00})^2 T_1 + z_{00} T_2 + k - W_3](z_{00}^2)$ will be satisfied at a lower level of training. Similarly if γ rises and age rises simultaneously the optimal level of T_1 will drop. Similar arguments prove the proposition for T_2^* as well as the remaining part of the proposition. QED

We now turn to discuss the impact of the firm's boundary on older workers' training.

2.2 The effect of changes in the firm's boundaries on older workers' training.

We can explore the impact on training of the possibility for a firm to outsource part of its activities. Let assume that if an external worker currently employed outside the technologically leading sector of the economy is employed in the TL firm, his/her skill is $z_{10} = (1+\gamma)^{-2\tau}$, a decreasing function of the rate of technological innovation γ as well as the measure of vintage specificity of skill.[1]

If outsourcing is available in period three, firms may substitute away from permanent workers towards contracted out labor services if $(\pi_3 - W_3) \leq (z_{10} - w)$ where π_3 and W_3 are defined as before, while w is the wage paid to contracted out workers. We assume that w is set competitively so the only requirement for a firm's to consider the outsourcing option is that $z_{10} - w > 0$. In period three the surplus derived from using

[1] Note that we are overlooking the effect of age on the skill of an external worker for empirical reason as it will become clear later on.

internal workers is now

$$S_3 = \frac{1}{4k}[(z_{00})^2 T_1 + z_{00}T_2 + k - W_3 - (z_{10} - w)]^2 \tag{7}$$

which is derived as before as the probability that the job is maintained in period 3, $Prob(\pi_3 - W_3) > (z_{10} - w)$ multiplied by the expected surplus in period 3, conditional on it being larger than $(z_{10} - w)$.

The first order conditions necessary for maximizing the expected surplus from training older workers are:

$$\partial S/\partial T_1 = \beta z_{00} - C'(T_1) + (\beta^2/4k)[(z_{00})^2 T_1 + z_{00}T_2 + k - W_3 +$$
$$-(z_{10} - w)](2z_{00}^2) = 0 \tag{8}$$
$$\partial S/\partial T_2 = -\beta C'(T_2) + (\beta^2/4k)[(z_{00})^2 T_1 + z_{00}T_2 + k - W_3 +$$
$$-(z_{10} - w)](2z_{00}) = 0 \tag{9}$$

From a simple inspection of the these two f.o.c.s it is straightforward to derive the following

Proposition 4

The availability of the option of outsourcing part of the firm's activities has effects on the optimal levels of training offered by a firm. In particular,

$$T_i^*|_{outsourcing} < T_i^*|_{without\ outsourcing}, i = 1, 2 \tag{10}$$

Also, note that this will still be the case even if W_3 endogenously adjusts to the external wage w so that $(W_3 - w) \simeq 0$, as long as $z_{10} > W_3$.

In the next sections I aim to test these propositions.

3 Testing the link between organizational changes and workers' training.

3.1 The data

Our econometric model estimates the probability of receiving employer-sponsored training in equilibrium.[2] I use the 1995 Australian Workplace Industrial Relations Survey (AWIRS 1995), which was conducted by the Federal Department of Employment, Workplace Relations and Small Business. It contains information regarding workplaces with 20 or more employees that represent a total of more than 37,000 workplaces in all industries except agricultural, forestry, fishing and defence. The AWIRS 1995 is a stratified random sample taken from official workplaces registers. The sampling frame was stratified on five employment size bands and 18 industry groups, thus providing 90 strata. Each workplace has two weighs associated with it. The first one corresponds to the number of workplaces it represents from its particular stratum. The second one indicates the number of employees (in the populations of workplaces with 20 or more employees) that each workplace represents. The workplace response rate was relatively high (80%). Although the unit of observation is the workplace (not a firm), an employee survey collected information regarding the workplaces' employees. The total number of employees interviewed is 19,155 that is well representative of the 3.6 million of people working in medium to large establishments (the response rate is 64%). It is important to stress that due to sampling design, employees are not made representative of the workplace itself. The availability of published

[2] Bassanini and Ok (2006) explain why, in practice, it is not easy to solve the identification and estimation problems surrounding a model of training demand and supply.

full information on the AWIRS sampling design means that I was able to conduct a design-based analysis, which accounts for weights, clustering and stratification.

3.2 Measuring workers' training.

The AWIRS dataset contains a number of measures of training activity. These include the employer's provision of formal training to employees in the previous year; funding of study leave for non-managerial employees; existence or introduction of a formal training scheme; the occupational distribution of training. The 1995 questionnaire asks the following question in the employee questionnaire:

Has your employer provided you with any training to help you do your job over the last 12 months?

In the entire sample, almost 32 percent of employees answered "no" to this question, about 60 percent answered "yes" and the answer is missing for only 2 percent of the sample of employees. There are two main limitations of the training measures in the AWIRS. Firstly, there is no direct information on the provision of informal (on-the-job) training. This is unfortunate as most employer-provided training takes the form of informal training (Frazis et al. 1998). Secondly, as the training variables are categorical, no information is available on the intensity of training (i.e. the number of hours devoted to training, the number of employees concerned or the amount of training expenditure). These limitations notwithstanding, the available training variables allow a useful investigation of the effects of technological and organizational change on training opportunities.

3.3 Information on changes in workplace organization

The AWIRS dataset has been specifically designed to investigate the effect of organizational and market changes on industrial relations and more widely on the level of satisfaction, participation and opposition to those organizational changes by employees. It asks management and union's representatives specific questions about workplace restructuring processes. A set of questions refer to the changes that the workplace has introduced in the last two years. In particular, questions related to "the introduction of major reorganization of workplace structure (for example, changing the number of management levels, restructuring whole divisions, sections and so on)" lead to the construction of a dummy variable (*Organisational Restructuring=0,1),* which takes value one if the workplace manager answered positively to the question above. A positive answer to the question on "major changes to how non-managerial employees do their work (for example, changes in the range of tasks done, changes in the type of work done)". These questions lead to the construction of the following dummy variables" leads to a positive value of the dummy variable *(Task Restructuring=0,1).*

Some of the variable asked at the managerial level can be directly related to the use of outsourcing. For example, other questions focus on the effect of the most important of the changes above on the number of casual employees and contractors (*Casual workers up? Contractors up?*) and the number of permanent employees (whether it increased or decreased). The answers to these questions provided at the workplace levels are used to assess the impact of organizational change involving outsourcing and casualisation of the labour force on the extent of older workers' training.

3.4 Measuring technological change and diffusion

3.4.1 Technological innovation at the workplace level

The primary source of information on workplace technological change is a set of questions that were asked both to the general management and to the union delegate of the sampled workplaces, namely:

What changes happened in the last 2 years in this workplace?

1. Introduction of major new office technology

2. Introduction of new plant, machinery or equipment

3. Does this workplace engage in technological benchmarking?[3]

From these survey questions I construct dummy variables that take value one if the answer to the respective questions was positive.

3.4.2 Measuring technological change at the industry level

Using concordance tables to match ISIC classification codes used by the OECD STAN/ANBERD dataset and the ANZSIC classification code used in AWIRS I combine AWIRS information on technological change at the workplace level with industry specific measures of technological change (innovation and diffusion). As in Magnani (2006), we can measure how technologically advanced the industry of current employment is by relying on industry-specific R&D expenditure. In the *flow approach* originating from Terleckyj (1974), "own" technology is treated as a flow and measured by R&D intensities, that is by R&D expenditures over output or value added. As Griliches and Mairesse (1984) demonstrate,

[3] The relevant question is:
In which of these categories (including technology), does this workplace benchmark?

this is equivalent to setting the depreciation rate for R&D equal to zero. With this method, a proxy for the technology Ω_{it} used by industry i at time t is provided by $Rflow$ where

$$Rflow_{it} = \sum_{\tau} \left[\frac{R\&D \text{ expenditure}_{i,t-\tau}}{Output_{i,t-\tau}} \right] \tag{11}$$

As clearly stated in Griliches (1979), the level of knowledge in any one sector of the economy is not only derived from "own" (*direct)* R&D investments, but is also affected by the knowledge "imported" from other sectors. This is the process of technology diffusion where the distance between firm-specific technology and economy-wide technology is shortened as knowledge and technical expertise spread and are assimilated throughout the economy (OECD 1996). In the flow approach technology is treated as a flow measured by R&D expenditure over output or sales. Technology diffusion occurs by means of transactions of intermediate and capital inputs. In this framework, *embodied* technology diffusion is the introduction into production processes of machinery, equipment and components that incorporate new technology. To highlight the importance of technology flows of this kind, it is suffice to say that in advanced economies much newer technology is embodied in the capital goods that industries purchase to expand and improve production (OECD 1996).

According to the flow approach, indirect technology flows from one industry to another when the industry originating the R&D sells products (intermediate or capital goods) embodying its R&D to other industries to be used as inputs in their production processes. Thus, indirect

R&D is

$$IndirR\&D1_{it} = R\&D\_INT_{it} + R\&D\_CAP_{it} \tag{12}$$

where $R\&D\_INT_{it}$ is the R&D intensity embodied in intermediate goods and $R\&D\_CAP_{it}$ is the R&D intensity embodied in capital goods that flow to industry i at time t.[4] The technology diffusion measure becomes

$$IRflow_{it} = \sum_{\tau} \left[\frac{IndirR\&D1_{i,t-\tau}}{Output_{i,t-\tau}} \right] \tag{13}$$

Thus the higher $IRflow$ is, the lower is the technological difference between industry i and the rest of the economy ($|\Omega - \Omega_i|$).

Data on direct and indirect R&D expenditures and intensities for the Australian economy have been made available by OECD researchers and refer to a small subset of years (1968, 1974, 1986, 1989, 1993). Table 1 reports technology measures (direct and indirect R&D intensities and technology flows as measured by $R\&D(direct)_{i,t}$, $IndirR\&D1_{i,t}$, $Rflow$ and $IRflow$, respectively, for selected 2-digit Australian manufacturing industries. Abbas Valadkhani (2005) provides a concordance table to match ISIC classification codes used by the OECD STAN/ANBERD dataset and the ANZSIC classification code used in AWIRS. Table 1a provides a list of definitions of the main explanatory variables. Table 1b and Table 1c reports summary statistics for the main AWIRS variables and the industry-specific technological change measures discussed

[4] More precisely, in the indirect component of industry $R\&D$, the OECD distinguishes between embodied and disembodied technological diffusion. Disembodied technological diffusion involves the transmission of knowledge, technical expertise or technology in a way that does not imply the purchase of machinery and equipment incorporating new technology. Conversely embodied technology diffusion is the introduction into production processes of machinery, equipment and components that incorporate new technology. In this study we focus on the embodied indirect R&D.

above, respectively. Table 1d reports sample correlations measures. It highlights how

3.5 The econometric model

To estimate the effect of technological change on older workers' training I adopt a simple probit framework. In the reference period (usually a year) individual h will engage in workplace training (Y_{ht}=1) or not (Y_{ht}=0). Thus:

$$Y_{ht} = \begin{pmatrix} 1 \text{ if } Y^*_{ht} \geq 0 \\ 0 \text{ otherwise} \end{pmatrix} \tag{14}$$

$$Y^*_{ht} = X_{ht}\alpha + \delta Z_{hit} + TC_{hit} + \epsilon_{ht} \tag{15}$$

where X_{ht} is a vector of individual specific characteristics, Z_{hit} is a vector of characteristics of individual h's workplace i in time t, the vector TC_{hit} is a set of workplace specific variables that proxy for technological change in the workplace. The vector X_{ht} contains the following variables: age in brackets, gender, country of birth, number of dependents and other family members individual h may be caring for, a quadratic in tenure at the current workplace, hours of work per week, dummy variable for a fixed contract, education (highest degree achieved), occupation and job title, weekly/annual gross salary. We exclude from the sample those individuals affected by any disability. The vector Z_{hit} allows me to control for a number of factors that may affect the workplace decision regarding training, namely firm size, composition of the firm's workforce (by gender, occupational groups, type of employment arrangement) and the "propensity" to train as proxied by the number of employees who were trainees last year, the age of the business, the nature of the market in which the business is working, unionization at the workplace level, and whether the business is in the private sector or public sector.

Finally the vector TC_{hit} contains a number of variables that measure the nature of technological change (innovation and diffusion) in the workplace i of individual h at time t. As in Bartel et al., (1993) the effect of technological change on training may vary by education or occupation, so I will estimate the full specification above for separate groups of workers who differ by age.[5]

The main results are organized in five tables. Table 1 reports summary statistics of selected variables for employees (top panel) and for workplaces (bottom panel). Table 2 illustrates the effect of technological change on workers belonging to the full sample and to a sample of workers aged 45 and plus (*older* workers). Table 3 addresses the question of the effect of age on the likelihood of receiving training, by reporting regression results for subsample of older workers (45-49; 50-54; 55 and plus; 50 and plus). Table 4 includes among the explanatory variables the AWIRS measures of organizational change, namely (*Organisational Restructuring=0,1), (Task Restructuring=0,1),* (*Casual workers up?); (Contractors up?).* Table 5 tests again proposition 3 by disaggregating a sample of older workers along the age dimension.

3.6 Identification and robustness issues

One relevant identification issue that is worth discussing is that important explanatory variables *at the workplace level* could be endogenous. Blau and Shvydko (2006) find indirect support to the hypothesis that

[5] Note that the dummy variable for training in the last year may be a poor measure of investment in training as firms may decide to train older workers with less intensity rather than providing no training at all for this age category of workers.

technological change at the workplace level could be endogenous. Specifically they argue that establishments with a relatively large share of older workers, other things equal, should be less likely to use technology or employment practices that result in labor market rigidities. Also it is well established that training activities are one of the largest contributions to firms' fixed costs of employment (Hamermesh 1996). As such, it is distributed unevenly among workers who differ by labour market attachment (e.g., Booth et al., 2002). Secondly, training is likely to make firms less willing to provide hours flexibility as this would limit the firm's chance to profit from training its workforce. Thus even the propensity of a workplace to introduce training schemes could be fighted against by a relatively aged workforce.

By analyzing the association between the age composition of employment in an establishment and the rate at which workers of different ages separate from the establishment, they find strong and robust evidence that an older age structure of the work force at the establishment-level is associated with a lower separation propensity of its older workers, relative to the separation propensity of its younger workers. These results provide indirect but suggestive evidence of potential endogeneity of technological and organizational change.

These findings raise important identification issues. I address this issue by checking how the probability that a workers receives training responds to technological change measured both at the workplace level and at the industry level. By using an industry level measure of technological change merged establishment level dependent variables, it is reasonable to assume that workers and employers take these measures of technological change as exogenous rather than as resulting from endogenously determined strategies. This allows us to solve an important methodological difficulty often encountered in this type of exercises, namely the issue of how to identify the direction of causation between innovation and the composition of the workforce at the workplace level.

Finally, I test for endogeneity of the workplace variable that defines whether a workplace had introduced a training scheme in the last two years. Because such workplace variable is used as an explanatory variable in the employee-specific question on received training in the last year, a test of endogeneity allows to shed some light on the sorting of employees into workplaces (*Appendix I*, Table 6). These techniques allow me to test and discuss the robustness of the results reported in tables 2-5.

4 The empirical results

The empirical investigation of older workers' training has four main components: (i) whether indeed age impacts upon a worker's training opportunities after controlling for a number of features of the workplace environment that may affect its propensity to train. Note that this per se could be interpreted as a signal of (technical) skill obsolescence, the depreciation of capital that, as in Rosen (1976) derives from a reduction in human capital caused by physiological factors; (ii) whether a worker's general human capital positively affects his/her training chances; (iii) whether there is support to the idea of economic skill obsolescence, the reduction in value of the human capital as age progresses, for instance due to technological change; (iv) whether older workers' chances of getting trained are diminished by the reorganization of the workplace as captured by variables such as "*Organizational Restructuring*?", "*Task Restructuring?*", "*Causals up?*", "*Contractors up?*".

Starting from the first question, there is probably nothing new in stating that older workers, those aged 55 and plus appear indeed disadvantaged in their chances to receiving training. For example using the expected outcome resulting from the estimation results reported in Table 2, we find that being 55 or older reduces the probability of receiving employer's provided training from 0.64 to 0.54 and the reduction is statistically significant at the 99 percent level. A worker' general skill is important in determining the training result. In fact, the probability of getting training changes with the occupation the employee holds. For example being employed in non-production jobs is consistently positively correlated with training in all specifications. Holding a college degree or higher increases the chances of receiving training at all ages, a fact that sheds support to the idea of training/education complementarities. An important question that these results raise is whether such results are robust to the control of the pattern of technological change at the workplace as well as at the industry of employment level. This leads to the following central research question.

4.1 Does technological change impact upon workers' skill obsolescence?

There are two aspects of the results reported in table 2 that deserve attention. First of all, the hypothesis of skill obsolescence would receive some empirical support if we found a negative relationship between measures of technological innovation and training. Secondly, the analytical discussion carried out before has illustrated the hypothesis that technological change induces skill obsolescence may result in a continuum of effects as the worker's age increases. The empirical results illustrated in Table 2 show that in general technological change is found to significantly affect workers' training, although not always in an unequivocal way. Table 2 can address the first question. It shows that while the introduction of new office technology does not significantly impact on training, the introduction of new machinery reduces the likelihood of training by about 11% in the full sample, and by about 14 percent in a sample of older workers. Interestingly, whether a workplace benchmarks in technology boosts the chances of a worker's training in the full sample, but does not change an older worker's training opportunities. Technological change at the industry level affects older workers' training. While our measure of "own" technology decreases an older worker's chances of receiving training, our measure of technological diffusion (*IRflow*) has a positive impact on training.

In Table 3 we perform a disaggregation by age of the sample of older workers. Of the four different age groups considered (defined by the age groups 45-49; 50-54; 55 and plus, 50 and plus) the last two deserve particular attention. In all cases the comparison group is the sample of all workers aged 15 and older. In the case of workers aged 55 and plus it is noteworthy that all technological innovation variables are negatively signed implying a negative relationship between technological innovation and employer provided training. Of these three out of four are statistically significant at least at the 90 percent level. For example, the introduction of new office technology at the workplace level, has a positive and statistically significant coefficient in the full sample (*+0.114),* but it has a negative coefficient (*-0.363)* if a worker is 55 or older. Similarly, while the impact of technology benchmarking is positive in the full sample, it is negative in the sample of those aged 55 and plus. When we measure technological innovation at the industry level, it is important that Rflow has a negative and highly statistically significant coefficient in Specification III, where the interaction terms involve the age group "55 and plus". These results are confirmed when a sample of workers aged 50 and plus is considered, although the level of statistical significance is slightly lower. Interestingly, in both samples of older workers (those aged 55 and plus and those aged 50 and plus) our measure of technological diffusion (*IRflow*) shows a positive and statistically significant coefficient in training regressions, suggesting that technological diffusion increases workers' chances of receiving training.

Note that these results signal complex ways in which a workplace values human skills in the face or rapid organizational changes. The negative impact of technological innovation on older workers' training is broadly consistent with Proposition 1. In the context of our analysis it suggests that technological change may negatively impact on the evaluation that workplaces make of older workers' skill. Skill obsolescence in turn negatively impacts on the workplace decision to train its employees.

4.2 The impact of technological change on workers' training. Robustness.

Table 4 and Table 5 are useful to check the robustness of the results illustrated in the previous two tables. When we control for organizational restructuring there are a number of changes in the significance of the technology variables that are worth to mention. A comparison between Table 2 and Table 4 illustrates that, after controlling for organizational restructuring, *(i)* the introduction of new office technology significantly boosts workers' training opportunities in the full sample, although remains non-statistically significant in the sample of older (aged 45 and plus) workers; *(ii)* the introduction of new machinery does not affect training in any sample; *(iii)* industry-level technological change (innovation as measured by *Rflow*, and diffusion, as measured by *IRflow*) maintains its statistical significance, with negative and positive coefficients, respectively.

A decomposition of the sample of workers aged 45 and plus in subgroups by age is informative to check which groups are indeed the most affected by technological change. Table 5 shows that industry level technological change affects primarily the oldest of this age group, namely those aged 50 and plus or even more, those aged 55 and plus. Particularly for these two latter age groups we find robust evidence in support to the skill obsolescence hypothesis, as expressed by Proposition 1. The finding that our measure of technological diffusion (*IRflow*) has a positive impact on older workers' training can be interpreted in support to Proposition 2, which states a positive relationship between training and skill transferability, which in our setup increases as technology diffuses. It is also noteworthy that the size of the coefficients of the industry level technological change (*Rflow* increases significantly as we move from the older (50 and plus) to the oldest (55 and plus), a result that can be interpreted in support to Proposition 3, according to which the skill obsolescence effect of technological innovation increases with age.

Note that existing studies on the effect of technological and organizational changes on older workers' labour market opportunities are hardly able to control for potential endogeneity of the main explanatory variables. Beckmann (2004) uses lagged variables to draw robust evidence of age-biased technological and organizational change. In this sense the integration of the set of explanatory variables at the workplace level with industry level data is important as it overcomes the potentially biasing factor of endogenous technical change (Bartel and Sicherman; 1998). To further address this issue I consider the possibility that older workers select themselves into workplaces that are less likely to undergo technological and organizational change. If this is true, the workplace propensity to train its workforce could be endogenous and determined by factors that are potentially correlated with the error term in the individual training specification. IV regression results in Appendix I show that the negative impact of our industry level measure of technological change (*Rflow)* maintains its negative and statistically significant impact on older workers' training, an effect that is greatly magnified in the sample of those aged 55 and plus. Similarly our measure of technological diffusion (*IRflow*) has a positive impact (statistically significant at the 5 percent level) on the training opportunities of the oldest workers.

4.3 Workers' training and organizational restructuring.

A basic model analyzed in the previous section has pointed out that if there is substitutability between internal and external workers, the possibility of hiring external workers may decrease the training opportunities of internal workers. This naturally leads to the following question: Does the effect of organizational restructuring compound to the impact of technological change in reducing older workers training? We test Proposition 4 by means of detailed information on the restructuring of the workplace organization, changes in its hierarchical structure, changes in the job definition and the range of tasks employees are called to perform, in AWIRS workplaces.

We focus on Table 4 and Table 5, which has already revealed the usefulness of performing a disaggregation by age of the main sample. In general, these tables clearly illustrate that organizational restructuring has a *positive* impact on workers' training although the degree of statistically significance somehow varies. For example, of the AWIRS measures of organizational restructuring, both *task* and *hierarchical structure changes* positively affect workers' training opportunities in the full sample. Table 5 clearly shows that the redefinition of the job description, as indicated by the dummy variable *task restructuring,* significantly impacts on the training opportunities of those workers aged 50 and plus and even more so for those aged 55 and plus.

Changes in the boundaries of the workplace, as indicated by dummy variables for an increase in outsourcing and for an increase in casual workers do not significantly alter the chances of workers's training in any sample in table 4. Again a disaggregation by age reveals that there is substantial aggregation bias. In fact, when the number of contingent workers (casuals and/or contractors) increases, training for older workers, particularly those aged 55 and plus, becomes more available.

Note that none of these results are consistent with the hypothesis of substitutability between internal and "external" labour services. According to Proposition 4, which stems from such hypothesis, we should expect a *negative* impact of organizational change on workers' training. Conversely, these results are in general consistent with the view expressed for example by Lindbeck and Snower (2001), according to whom, increased functional flexibility and reduced task specialization *among workers* within a firm, brought in by a more narrow focus on a firm's "core competencies" in production and the outsourcing of "non-core competencies", have boosted all workers, but particularly oldest workers', training opportunities.

5 Final remarks and conclusions

This study has investigated the impact of technological and organizational changes on older workers' training. The model sketched in this study critically addresses important empirical questions regarding how workplace and industry changes shape the labour market opportunities of older workers. The main results can be summarized as follows:

1. Age significantly affects training opportunities, decreasing the training chances particularly for those workers aged 55 and plus. This is so even after controlling for a large number of individual-specific, workplace-specific and industry-specific variables.

2. This study finds very little support to the hypothesis of economic skill obsolescence in a full sample of workers aged 15 and plus. Technological innovation at the workplace level, particularly the introduction of new office technology and the workplace technological benchmarking *increase* rather than decreasing workers' training opportunities. Industry level technological change does not affect workers' training in the full sample.

3. Industry level technological innovation significantly *reduces* the oldest workers' training (aged 55 and plus and aged 50 and plus). This result is robust to the control for organizational restructuring and to changes in the econometric specification.

4. Industry level technological diffusion *increases* the chances of the oldest workers' training, but it does not significantly affect workers' training in other age groups.

5. The workplace task restructuring has a positive effect on workers' training. This effect is the largest among the most senior workers.

6 Contrary to our expectation, which was based on a hypothesis of substitutability between internal and external workers, the expanded use of alternative employment arrangements (casuals and outsourcing) increases the training opportunities for workers aged 55 and plus and to a less extent, for workers aged 50 and plus.

Note that results 2 and 4 are broadly consistent with Bresnahan et al. (2002) who find strong complementaritis between skilled labour and some types of firm level changes including new work organisation and new products and services. Results 5 appears in tune with Cairoli et al. (2001) who find that organisational change (which in their definition includes "increased multitasking") has a positive impact on quantities demanded, prices and productivity of skilled workers. Result 6 also deserve some comment. A finding that the increased use of casuals and outsourcing has a positive impact on training for older workers (those who are likely to have a higher level of firm-specific skill relative to external workers, is consistent with Cairoli et al., (2001)'s finding according to whom organizational change defined as (a) decentralisation of authority, (b) delayering of managerial functions are skill complements.

However this study originally contributes to our knowledge on the effect of organizational and technological changes on older workers labour market opportunities. In particular, this study documents robust evidence that technological change, particularly if measured *at the industry level,* may indeed cause some skill obsolescence among older workers, properly defined. Although this study is not directly interested in assessing the impact of IT applications and innovative organisational practices, these results are broadly consistent with Aubert, Caroli and Roger (2006) who find a negative effect on the employment growth of older workers. By distinguishing between industry level and workplace level technological changes, this study is able to overcome the likely endogeneity of technological change at the workplace level argued for example by Blau et al. (2006). While the impact of workplace level innovation is likely to be underestimated, given that workplaces with a relatively large share of "older" workers may resist change, the use of a industry-specific measure of technological innovation is particularly suitable to address the focal question of this study. Lastly, this study originally contributes to the literature by finding sizeable differences in the way the two faces of technological change, namely innovaiton and diffusion, impact upon older workers' training opportunities. A finding that older individuals in industries undergoing technological change have lower chances of receiving training may suggest that these workers also have shorter working careers. If the exit from the labour force is due to economic skill obsolescence, retirement may indeed be an optimal solution from the societal point of view, only provided we have grounds to believe that firms indeed choose the first best level of training. Although the existing literature does not allow us to make a strong argument for under-provision of training (Bassanini et al., 2005) the results that technological diffusion positively impacts on the training opportunities for older workers suggest that technological diffusion may be the focus of training/technology policies which reduce social exclusion, particularly in the face of substantially longer expected lives.

Finally, although this study is unable to accurately test for hypothesis concerning *time changes* in the training gaps existing between younger and older workers, the findings of this study suggest that two important trends observed in the last few decades may contribute to explain why the extent of the size of the gap in training participation between older adults and younger adults, although still relatively large, has been declining over time (OECD, 1998). Both the increasing extent of workplace restructuring, with the consequent changes in the definition and mix of workers' skills, and the intensification of technological diffusion, brought by the tightening of the input linkages between industries (OECD, 1996), would predict a reduction in the relative disadvantage that older workers experience in terms of training opportunities.

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Table 1a: Definitions of the main technological and organizational change variables

Employer-provided training	dummy variable=1 if "yes" to "*Has your employer provided you with any training to help you do your job over the last 12 months?*
Technological Change	
New office equipment	=1 if a workplace has introduced new office equipment in the last two years
New machinery	=1 if a workplace has introduced new plants, machinery or equipment in the last 2 years
Technology benchmarking	=1 if a workplace has engaged in technology benchmarking in the last 2 years
Industrial Technology	
Own technology (Rflow)*	See equation (11) and related explanation in the text
Indirect technology (IRflow)*	See equation (13) and related explanation in the text
Organisational Change	
Task restructuring	=1 if there has been major changes in the range of tasks done or changes in the type of work done
Organisational restructuring	=1 if there has been a major reorganization of workplace structure (e.g., changes in the number of management levels, restructuring of whole divisions or sections) in the last 2 years
Use of casual employees up	=1 if there has been an increase in the number of casual workers employed in the last 2 years
Use of contractors up	=1 if there has been an increase in the number of contractors employed in the last 2 years

Table 1b: Weighted Means of main variables by age groups.

	Full sample	Age 45-49	Age 50-54	Age 55+
Employer-provided training	0.67	0.69	0.64	0.54
Technological Change				
New office equipment	0.13	0.13	0.11	0.1
New machinery	0.13	0.13	0.17	0.18
Technology benchmarking	0.44	0.44	0.43	0.48
Industrial Technology				
Own technology (Rflow)*	0.24 (0.01)	0.23 (0.02)	0.30 (0.03)	0.26 (0.03)
Indirect technology (IRflow)*	0.85 (0.01)	0.81 (0.03)	0.78 (0.03)	0.72 (0.03)
Organisational Change				
Task restructuring	0.21	0.2	0.22	0.26
Organisational restructuring	0.43	0.44	0.4	0.38
Use of casual employees up	0.17	0.16	0.17	0.15
Use of contractors up	0.04	0.05	0.03	0.05
	0.31	0.33	0.31	0.34
Market Competition				
Intense competition	0.39	0.37	0.39	0.36
Strong competition	0.33	0.3	0.32	0.36
Moderate competition	0.08	0.09	0.08	0.07
Some competition	0.02	0.03	0.01	0.02
Limited competition	0.02	0.03	0.03	0.04
Workplace Training	0.65	0.66	0.59	0.5
Training in last 2 years	0.42	0.44	0.4	0.45

Note: * continuous variable, standard deviation in parentheses

Table 1c: Summary Statistics for technology flows, 2-digit ANZSIC industries

Selected 2-digit manuf. industries	ANZSIC	$Rflow$	$IRflow$
Coal mining	11	0	1.32
Food, Beverages and Tobacco	21	1.19	0.9
Textile, Clothing, Footwear and Leather	22	0.4	0.69
Wood and Paper products	23	0.5	0.97
Printing, Publishing and Recorded Media	24	0.99	1.13
Petroleum, Coal, Chemical and Ass. Prod.	25	0.06	0.013
Non-metallic Mineral Product	26	3.38	0.75
Metal Product Manufacturing	27	0.03	0.01
Machinery and Equipment	28	0.16	0.015
General Construction	41	0	2.49
Communication Services	71	0	1.66
Financial services	73	0	1.32

Table 1d: Sample correlations among main explanatory variables: technological change and organizational change

	new off. equip.	new mach.	tech. bench.	RYflow	IRYflow	contractors up?	casuals up?	task restruc.	org. restruc.	training sc. < 2 years
new off. equip.	1.0000									
new mach.	-0.1612	1.0000								
tech. bench.	-0.0211	0.0556	1.0000							
RYflow	-0.0784	0.1339	0.0124	1.0000						
IRYflow	0.0288	-0.0172	-0.0679	0.4641	1.0000					
contractors up?	-0.0370	-0.0119	0.0181	-0.0488	-0.0407	1.0000				
casuals up?	-0.0156	0.0201	0.0044	-0.0638	-0.0606	0.0899	1.0000			
task restruc.	-0.2074	-0.1983	0.0418	-0.0208	-0.0077	-0.0008	-0.0166	1.0000		
org. restruc.	-0.4864	-0.4651	0.0556	-0.0631	-0.0596	0.1368	0.1111	0.4264	1.0000	
training scheme <2 years	-0.0220	0.0245	0.0181	-0.0361	-0.0292	-0.0082	0.0158	0.0817	0.0791	1.0000

Table 2: Weighted[a] Probit Estimation of Training for Older Workers (aged 45 and plus) compared to full sample

Explanatory variables	Full sample results			Older workers' results		
	Coeffic.	S.E.	Margin.	Coeffic.	S.E.	Margin.
Individual-specific						
Male	-0.038	(0.044)	-0.014	0.018	(0.095)	0.006
Age 15-20	0.376***	(0.089)	0.130***	___		___
Age 21-24	0.111	(0.080)	0.041	___		___
Age 30-34	-0.051	(0.073)	-0.019	___		___
Age 35-39	-0.036	(0.075)	-0.014	___		___
Age 40-44	0.066	(0.076)	0.024	___		___
Age 45-49	0.135*	(0.081)	0.049*			___
Age 50-54	-0.041	(0.089)	-0.015	-0.179**	(0.091)	-0.061*
Age 55 and plus	-0.264***	(0.100)	-0.102***	-0.397***	(0.102)	-0.141***
Tenure	-0.038***	(0.008)	-0.014***	-0.007	(0.013)	-0.002
Tenure^2	0.001***	(0.0003)	0.0004***	0.0003	(0.0004)	0.00008
Full-timer (hours ≥ 35)	0.116*	(0.059)	0.044*	-0.144	(0.134)	-0.045
Non-production	0.297***	(0.059)	0.107***	0.364***	(0.116)	0.117***
High School diploma	0.056	(0.053)	0.021	0.155	(0.112)	0.048
Vocational training	-0.003	(0.056)	-0.001	-0.050	(0.109)	-0.016
Undergrad. degree	0.271***	(0.085)	0.096***	0.334*	(0.193)	0.099*
Diploma	0.066	(0.079)	0.024	0.174	(0.172)	0.053
Postgraduate degree	0.268**	(0.115)	0.094**	0.170	(0.234)	0.052
Fixed contract	0.135	(0.095)	0.049	0.073	(0.187)	0.023
Workplace-specific						
Private sector	-0.128*	(0.071)	-0.047*	-0.188	(0.138)	-0.060
Size	0.00002	(0.00007)	0.000007	0.000005	(0.0001)	0.000002
Training scheme < 2 years	0.079**	(0.040)	0.029**	0.051	(0.078)	0.016

Table 2 cont'd: Weighted[a] Probit Estimation of Training for Older Workers (aged 45 and plus)

Explanatory variables	Full sample			Older workers		
	Coeffic.	S.E.	Margin.	Coeffic.	S.E.	Margin.
Market competition						
Import competition	0.162***	(0.041)	0.060***	0.267***	(0.085)	0.086***
Intense competition	-0.233**	(0.090)	-0.087**	-0.128	(0.176)	-0.042
Strong competition	-0.259***	(0.091)	-0.098***	-0.070	(0.176)	-0.023
Moderate competition	-0.192*	(0.105)	-0.073*	-0.137	(0.210)	-0.046
Some competition	-0.098	(0.147)	-0.037	0.106	(0.286)	0.032
Technological change						
New Office Technology?	0.071	(0.055)	0.026	0.008	(0.118)	0.002
Workplace New Machinery?	-0.295***	(0.053)	-0.113***	-0.399***	(0.104)	-0.140***
Workplace Tech. Bench.?	0.125***	(0.040)	0.046***	0.067	(0.080)	0.021
Own technology $Rflow$	-0.036	(0.027)	-0.013	-0.152**	(0.053)	-0.049***
Indirect technology $IRflow$	0.027	(0.030)	0.010	0.153**	(0.061)	0.049**
No. Observations	6902		-	1696		-
F-test	8.61***		-	3.85***		-

Table 3: Weighted[a] Estimation for the Probability of Training: Sample of workers of all ages, "older workers" differently specified.

Technological change variables	Age group 45-49	Age group 50-54	Age group 55 and plus	Age group 50 and plus
New Office Technology?	0.088	0.092	0.114**	0.115**
	(0.057)	(0.057)	(0.056)	(0.058)
Workplace New Machinery?	-0.306***	-0.259***	-0.279***	-0.234***
	(0.056)	(0.055)	(0.055)	(0.058)
Workplace Techn. Benchmarking?	0.109***	0.125***	0.136***	0.146***
	(0.041)	(0.041)	(0.040)	(0.042)
Own technology $Rflow$	-0.028	-0.042	-0.222	-0.022
	(0.028)	(0.027)	(0.027)	(0.028)
Indirect technology $IRflow$	0.023	0.023	0.014	0.007
	(0.031)	(0.030)	(0.030)	(0.031)
Age Group*New Office Techn.	0.067	0.037	-0.477*	-0.163
	(0.178)	(0.194)	(0.244)	(0.155)
Age Group*WP New Machinery?	0.085	-0.380	-0.228	-0.380***
	(0.167)	(0.186**)	(0.208)	(0.144)
Age Group*WP Techn. Bench.	0.121	-0.085	-0.264*	-0.207**
	(0.106)	(0.118)	(0.144)	(0.094)
Age Group*$Rflow$	-0.091	0.027	-0.372***	-0.104
	(0.077)	(0.082)	(0.144)	(0.071)
Age Group*$IRflow$	0.042	0.067	0.240**	0.147**
	(0.073)	(0.082)	(0.115)	(0.068)
No. Observations	6902	6902	6902	6902
F-test	7.96***	8.00***	8.24***	8.47***

Table 4: Weighted[a] Probit Estimation of Training for Older Workers (aged 45 and plus) compared to full sample: technological and organizational change.

Explanatory variables	Full sample		Older workers	
	Coeffic.	Margin.	Coeffic.	Margin.
Technological change				
New Office Technology?	0.295***	0.104***	0.172	0.053
	(0.071)	(0.023)	(0.153)	(0.045)
New Machinery?	-0.062	-0.023	-0.206	-0.070
	(0.071)	(0.026)	(0.146)	(0.052)
Technological Benchmarking?	0.106***	0.039***	0.049	0.016
	(0.040)	(0.014)	(0.080)	(0.025)
RY1995	-0.022	-0.008	-0.129**	-0.041**
	(0.026)	(0.009)	(0.052)	(0.017)
IRY1995	0.020	0.007	0.140**	0.045**
	(0.030)	(0.011)	(0.061)	(0.02)
Organizational change				
Any organizational restructuring?	0.214***	0.080***	0.125	0.041
	(0.062)	(0.023)	(0.130)	(0.043)
Any task restructuring?	0.169***	0.062***	0.218**	0.067**
	(0.056)	(0.020)	(0.111)	(0.033)
Use of casuals up?	0.080	0.029	0.148	0.046
	(0.055)	(0.020)	(0.110)	(0.033)
Use of contractors up?	0.045	0.016	0.127	0.041
	(0.048)	(0.017)	(0.092)	(0.029)
No. observations	6902	-	7235	-
F-test	8.59***	-	3.68***	-

Table 5: (Weighted)[a] probit estimation of the probability of training. Disaggregation of the sample of older workers in age groups.

Explanatory variables	*Age 45-49*	*Age 50-54*	*Age 55+*	*Age 50+*
Worplace Technological change				
New office equipment	-0.037	0.727***	-0.268	0.320
	(0.238)	(0.266)	(0.333)	(0.199)
New machinery	-0.353	0.026	-0.111	-0.059
	(0.222)	(0.253)	(0.323)	(0.194)
Technology benchmarking	0.123	-0.034	0.025	0.001
	(0.123)	(0.146)	(0.166)	(0.104)
Industry technology				
Own technology ($Rflow$)	-0.104	-0.024	-0.353**	-0.124*
	(0.078)	(0.083)	(0.144)	(0.073)
indirect technology ($IRflow$)	0.044	0.066	0.530***	0.207**
	(0.089)	(0.111)	(0.154)	(0.089)
Organizational change				
Any organizational restructuring	-0.131	0.696***	-0.238	0.272
	(0.198)	(0.233)	(0.289)	(0.174)
Any task restructuring	0.162	0.151	0.490**	0.295**
	(0.166)	(0.215)	(0.233)	(0.151)
Use of casual employees up?	0.052	0.022	0.573**	0.243*
	(0.170)	(0.196)	(0.237)	(0.146)
Use of contractors up?	0.115	-0.030	0.455**	0.191
	(0.140)	(0.163)	(0.190)	(0.122)
No. of observations	7383	7392	7364	7304
F-test	2.42***	1.91***	1.80***	2.46***

Appendix I.

Table 6: Instrumental Variables (IV) regressions for training when "Workplace Training Scheme in the last two years" is endogenous.

Selected explanatory variables	*Full Sample*		*Age 45+*		*Age 55+*	
	Coeffic.	S.E.	Coeffic.	S.E.	Coeffic.	S.E.
Workplace-specific						
Training program < 2 years	-0.965***	(0.179)	-0.592	(0.495)	1.079*	(0.576)
WP Techn. Change						
New Office equipment	0.376***	(0.055)	0.365***	(0.129)	-0.108	(0.241)
New Machinery	0.220***	(0.061)	0.126	(0.169)	-0.208	(0.224)
Techn. Benchmarking	0.068**	(0.030)	0.041	(0.063)	0.022	(0.127)
Industry Technology						
Own Technology	-0.038*	(0.021)	-0.083**	(0.042)	-0.229**	(0.101)
Indirect Technology	-0.009	(0.022)	0.042	(0.048)	0.251**	(0.100)
Organizational Change						
Any organ. restructuring	0.416***	(0.050)	0.337**	(0.145)	-0.380*	(0.220)
Any task restructuring	0.110***	(0.042)	0.156*	(0.087)	0.293	(0.188)
Use of casuals up?	0.059	(0.044)	0.065	(0.091)	0.318*	(0.184)
Use of contractors up?	0.080*	(0.036)	0.144*	(0.073)	0.250*	(0.144)
modified rho	0.572***	(0.115)	0.360	(0.267)	-0.545	(0.379)
Wald test of exog. Prob>χ^2	0.00		0.177		0.151	
No. of observations	6999		1731		422	
Log-likelihood	-9227.16		-2305.77		-560.18	