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TECHNOLOGICAL CHANGE AND OLDER WORKERS' TRAINING

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ABSTRACT

The aim of this paper is to investigate how technological innovation and diffusion affects the training opportunities of older workers. Since the early 1970s, technological change has been a key factor in the re-organisation of the firm. A simple theoretical framework allows me to consider a firm that hires and trains workers. The model shows how the features of technological change shape the firm's training decision. In the second part of the paper I use a detailed matched employer-employee Australian survey, AWIRS (1995), to provide some evidence of how technological innovation and diffusion impacts upon the training opportunities of older workers. Among the most interesting results is evidence that older individuals, particularly those aged 55 and plus, employed in industries undergoing technological change have lower training opportunities. This result suggests that predictions regarding skill shortages in Australia may not be overly pessimistic.

Key words: *Older workers, Technological Change, Innovation, Diffusion, Skill Shortage.*
JEL Classification: J0, J2,O3

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TECHNOLOGICAL CHANGE AND OLDER WORKERS' TRAINING

1. INTRODUCTION

Population aging is profoundly changing the composition of the labour force in OECD countries. In Australia the share of young people in the labour force is projected to fall from around 38 to 31.6 percent, while the proportion of people aged 55 to 64 will more than double from 5.3 percent to 11.2 percent over the next thirty years (Chapman and Kapuscinski, 2001). One of the most striking paradoxes of today's OECD societies is that, although people live longer, they do not tend to retire later. One possible explanation for this relies on the limited demand for older workers, which to some extent remains largely unexplored. It is only recently that the literature has started addressing the causes of the relatively narrow range of job opportunities available to older workers and its impact on labour market participation. Older workers are often forced to move across job situations because the characteristics of the job chosen in early years are not suitable anymore (Ruhm, 1990). Furthermore, older workers may want to reduce hours of work to make the transition into retirement smoother (Doeringer, 1990). Lastly, the training opportunities accessible to older workers are notably more limited than for younger workers, a fact that contributes to limiting the labour market opportunities of the most senior members of the labour force (OECD, 1998). This study investigates older workers' (aged 45 and older) training decisions when the firm faces rapid technological change. After deriving a few empirical predictions from a simple theoretical model, it tests them by means of an employer-employee matched data, the Australian AWIRS 1995. The paper is organised as follows. Section two discusses what is known about the impact of technological and organisational change on older workers' labour market opportunities. Section three reports the few known stylised facts on older workers' training and its determinants and introduces a simple model that will guide my discussion of the plausible impact of technological change on training. Section four describes the data set. Section five introduces the empirical specification. After discussing the empirical results section six draws some policy implications. Section seven discusses some policy implications of this analysis, while section eight concludes.

2. TECHNOLOGICAL CHANGE AND TRAINING

It is well known that the aging of the population has been accompanied by extremely rapid technological change. Technological change *per se* has been the single most important factor of change in labour demand in recent decades. It has led to a dramatic change in the structure of wages (Katz et al., 1992) and to the returns on education and experience (Allen, 2001). There exist arguments that rely on technological change in explaining the observed increasing wage inequality (Violante, 2002). Lastly, there is evidence that technological change affects a worker's decision to retire (e.g., Bartel and Sicherman, 1993). However, the literature has dramatically overlooked the effect of technological change on older workers' employment and the way in which it can change the willingness of employers to provide work practices suitable to this increasingly important population cohort.

The impact of technological change upon the labour market opportunities of older workers is inseparable from another issue - that is, the willingness of firms to train and retrain such workers to use new technologies. It is well established that training activities are one of the largest contributions to firms' fixed costs of employment (Hamermesh, 1995). As such, it is distributed unevenly among workers who differ by labour market attachment (e.g., Booth et al., 2002).

Finally, employers often have to decide whether to make additional investments in training or to purchase skill from outside. Whether training is firm specific or general, and thus whether it contributes to employees' transferable skill, depends on the degree of diffusion of the existing technology, which also increases the chances of finding suitable skills outside the firm. Thus patterns of technological innovation and diffusion may impact upon the provision of flexibility in working time to senior workers.

3. OLDER WORKERS AND TRAINING: WHAT DO WE KNOW?

Two important stylised facts motivate this study. Firstly, older workers are at a relative disadvantage in terms of accessing formal types of training in the workplace. Mostly using the Australian Bureau of Statistics (ABS) Surveys of Training and Education Experience undertaken by the ABS in 1989, 1993, 1997 and 2001, Wooden (1995) has shown that it is only the oldest cohort–aged 55 to 64 years–who appear to be at a sizeable disadvantage in terms of training. This is consistent with what OECD (1998) reports. A number of studies have also found that in contrast to unstructured training, the relationship between worker age and training incidence is curvilinear when more formal forms of training are considered. Both younger and older workers appear to be less likely to obtain training than their mid-career counterparts (see Wooden et al., (2001) and related citations). 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 in Australia, has been declining over time.

The sources of this change, however, are not immediately obvious. This study attempts to fill this gap by exploring the impact of technological innovation and diffusion on older workers' training. Economic theory does not provide a clear prediction on the sign of the relationship between technological change and training. One argument is that technological change makes education and previously acquired skill obsolete, thus making training less likely. Technological change may also increase the uncertainty of the return of investment in human capital thus decreasing training. Also, it may trigger a labour supply response which is particularly important in understand the training of older workers. In general the complementarity between training and schooling dominates the substitutability. Bartel et al., (1993) argue that if technological change is a "surprise", older workers are unlikely to desire training. In this case, technological change induces retirement. These considerations motivate the analysis I conduct in the next section.

3.1. The model

The first aim of the model is to investigate how the pace of technological change, both in terms of innovation and diffusion, 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 emphasised 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" (Wooden et al., 2001). In this "cooperative" game, training is chosen to maximise 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 formalised 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} t the beginning of period 2. As in Violante (2002), $z_{00} = (1+\gamma)^{-\tau}$ which implies that skills depend on the degree γ, γ > 0, of innovation from "new" machines of different generations and on the transferability of human capital τ between technologies of different age. Note that for any given level of γ, the higher τ , τ > 0 the less workers' skill is transferable across two subsequent vintages of machines. In other words τ is a measure of how specific vintage-specific skill is. I interpret this parameter as the effect of technological diffusion in the sense that the more vintage specific skill is the less technology diffuses. Note that the model does not distinguish between blue and white collar workers. There are two reasons for this. First of all the distinction between blue and white collar workers has been found particularly relevant in relation to Information and Communication Technology (ICT) changes. However, the measures of technological change this study makes use of, are not so specific and so they are unsuitable to study the impact of ICT on the firm's training decisions. Secondly, the literature has used the distinction between production and non-production workers as a proxy for skilled/unskilled workers (e.g., Berman et al., 1998), to the extent it is likely that important complementarities exist between general human capital (say education) and a firm's training decisions. Ignoring such a distinction allows me to focus on how a feature of technological change, namely innovation and diffusion, impact upon the training opportunities available to older workers without worrying about the related issue of how to invest in education.[1]

In period two, "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), i=*1,2*. In period 3, the productivity of "old workers" π_3 is affected by the shock ε as follows:

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

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

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

where $W_i, i = 1, 2, 3$ are the wages paid to a worker in period *i*. Note that the surplus in period three is the product of the probability that the job is maintained in period three, multiplied by the expected surplus in period three, conditional on it being positive. We write the probability of maintaining a job in period three as $\Pr ob(\pi_3 \geq W_3) = \Pr ob((z_{00})^2 T_1 + z_{00} T_2 + \varepsilon \geq W_3) = \frac{k - W_3 (z_{00})^2 T_1 + z_{00} T_2}{2k}$. In

[1] A useful starting point to differentiate between blue and white collar workers in this analytical framework would be to introduce a production function and formalise the worker's skill z_{00} in relation to the other inputs, primarily capital.

order 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 maximise 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:

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

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

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

Proposition 1

The optimal levels of training to "older" worker and to "old" workers, 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 $C'(T_1) = \beta z_{00} + \left(\beta^2/2k\right)\left[(z_{00})^2 T_1 + z_{00}T_2 + k - W_3\right]\left(z_{00}^2\right)$. 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 $\left(\beta^2/2k\right)\left[z_{00}T_2 + k - W_3\right]\left(z_{00}^2\right)$. 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 to "older" workers and to "old" workers, T_1^* and T_2^*, respectively, increase as technology diffuses (τ drops) and workers' skill becomes less vintage specific.

Proof. From the f.o.c. (4), note that $C'(T_1) = \beta z_{00} + \left(\beta^2/2k\right)\left[(z_{00})^2 T_1 + z_{00}T_2 + k - W_3\right]\left(z_{00}^2\right)$. 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 $\left(\beta^2/2k\right)\left[z_{00}T_2 + k - W_3\right]\left(z_{00}^2\right)$. For this reason the optimal level of T_1 will increase. A similar argument proves the proposition for T_2^*. QED

Proposition 3

For any given optimal level of training T_1^*, an increase in the rate of technological change γ has an ambiguous effect on older workers' optimal training T_2^*. *Proof.* Combining the two f.o.c.s we get:

$$C'\left(T_2^*\right)=\left[\frac{C'\left(T_1^*\right)}{\left(z_{00}\right)^2}-\frac{\beta}{z_{00}}\right] \tag{6}$$

Differentiating with respect to γ, we obtain:

$dC'\left(T_2^*\right)/d\gamma=\left[-\frac{2C'\left(T_1^*\right)}{\left(z_{00}\right)^3}\left(dz_{00}/d\gamma\right)+\frac{\beta}{\left(z_{00}\right)^2}\left(dz_{00}/d\gamma\right)\right]$ 0. In the right hand side, the second addendum is unambiguously negative, but the first item is positive. Thus for any optimal level of training in period one, T_1^* the optimal level of period two training T_2^* can increase or decrease following a rise in γ. QED

Proposition 4

For any given optimal level of training T_1^*, an increase in the skill transferability (a drop in τ) has ambiguous effects on older workers' training T_2^*.

Proof. Using expression (6) and proceeding as for proposition 3.

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 study explores the hypothesis that the pattern of technological innovation and diffusion affects the relative position of older workers in terms of access to training opportunities. In particular, this study aims to test the following implications of the model described above:

- Technological innovation reduces the employer's incentive to train employees
- If skill obsolescence in young and older workers differ, technological innovation will have a differential impact of training opportunities of workers who differ by age
- Technological diffusion increases the firm's incentive to train
- At the workplace level, the share of older workers changes the incentive to train

4. THE DATA

For this study I will 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 to 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. 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 people working in medium to large establishments. It is important to stress that due to sampling design, employees are not made representative of the workplace itself.

The AWIRS data contain a number of measures of training activity. These include: the 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; and the occupational distribution of training.

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 offer a multidimensional view of the process of technological change occurring at the firm level.

4.1. Measuring technological change and diffusion

4.1.1. Technological change at the workplace level

The primary source of information on workplace technological change is a couple of questions that were asked both to the general management and to the union delegate of the workplace of individual h's current employment, namely:

Section F, question F1: 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. Major reorganisation of workplace structure (for example, in the number of management levels)

4. Major changes to how non-managerial employees do their work (for example, changes in the range of tasks done).

Other proxies for technological change are provided by the information on the existence of technology benchmarking. The relevant question is:

Section D, question D7: In which of these categories (including technology), does this workplace benchmark?

The variable (*Workplace Technology Benchmarking = 0, 1*) is a dummy that assumes value one if the general management representative answers yes to the technology benchmarking question above.

4.2. Measuring technology and technological change at the industry level

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, 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

$$Rflow_{it} = \sum_{\tau} \left[\frac{R\&D\, expenditure_{i,t-\tau}}{Output_{i,t-\tau}} \right] \tag{7}$$

4.2.1. Measures of technological diffusion

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

$$IndirR\&D1_{it} = R\&D\_INT_{it} + R\&D\_CAP_{it} \tag{8}$$

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*.[2] The technology diffusion measure becomes

$$IRflow_{it} = \sum_{\tau}\left[\frac{IndirR\&D1_{i,t-\tau}}{Output_{i,t-\tau}}\right] \tag{9}$$

Thus the higher *IRflow* is, the lower the technological difference between industry *i* and the rest of the economy is.

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 2 reports technology measures (direct and indirect R&D intensities) and technology flows as measured by $R\&D(direct)_{i,t}$, $IndirR\&D1_{i,t}$, *Rf low* and *IRf low*, 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.

4.3. Relevant individual-specific variables

A number of studies have highlighted that the relationship between age and training incidence is strongest among men (for example, Miller, 1994; Green, 1993). Other variables that are known to be associated with training incidence and that are also thought to be related to age include education, hours of work and employment status, experience and job tenure, firm size, occupation and industry. Those workers with higher levels of educational attainment are more likely to receive training in the

[2] 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.

workplace (e.g., Bartel and Sicherman, 1993). Older workers are relatively more likely to be employed in occupations requiring high skills, such as managers, professionals and associated professionals. In fact, a large set of studies suggest that workers in more "skilled" occupations have a higher probability of gaining training (e.g., Baker &Wooden 1992a; Green 1993a; Groot 1997; Shields & Price 1996). Hours of work are also important in affecting the observed age-training profile. Part-time employment is most common among both younger and older workers, and is associated with a lower likelihood of participation in training (Baker & Wooden 1992a; Groot 1997), especially amongst women (Booth 1991; Green 1993). Furthermore, Australian studies have consistently found that casual employment is negatively associated with training incidence (e.g., Miller 1994).

4.4. Relevant workplace and industry-specific variables

Firm size is important in determining older workers' access to training. Older workers (especially those aged 45 to 54 years) are somewhat more likely than younger workers to be employed in larger firms (Wooden 1996), and at the same time, workers in larger firms are more likely to participate in training (Baker & Wooden 1995/96; Groot 1997; Wooden 1996). Another important variable is likely to be industry. Older workers are usually assumed to be over-represented in declining industries and thus most exposed to displacement. The benefits to employers in these industries from providing such training are likely to be relatively small.

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:

$$Y_{ht} = \begin{pmatrix} 1\, if\ Y_{ht}^{*} \geq 0 \\ 0\, otherwise \end{pmatrix} \tag{10}$$

$$Y_{ht}^{*} = X_{ht}\alpha + \delta Z_{hit} + TC_{hit} + \varepsilon_{ht} \tag{11}$$

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, maximum labour market experience defined as (AGE-EDUCATION-6) and its square, 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 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, unionisation 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., (1998) 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.[3]

6. THE EMPIRICAL RESULTS

Table 3 and Table 4 reports weighted probit regression results for the probability of training using matched employer-employee variables for the full sample of AWIRS 1995 workers and a selected sample of older employees (aged 45 and older), respectively. In both tables, training is explained by 3 sets of variables, namely:

1. individual-specific characteristics;

2. workplace-specific variables (whether in the private sector, the workplace size, whether the workplace has introduced a training scheme in the last two years),

3. market-specific variables that capture the extent of technological change in the workplace(new machinery in the last two years, workplace technology benchmarking) and in the industry of current employment (direct technology flow as measures by *Rflow* in expression (7), and indirect technology flow as measured by *IRflow* in (9)).

The impact of most of these variables on training using the AWIRS 1995 dataset has already been analysed by Wooden et al., (2001). This study, however, does not focus specifically on the impact of technological changes on the probability of older workers' training, although it discusses at length issues related to the determinant of training and to the satisfaction that employees feel about the way they are trained. Table 3 and Table 4 examine these issues in more detail.

The main results can be summarised as follows. Table 3 confirms the finding according to which workers aged 55 and plus are particularly disadvantaged in terms of training opportunities. Tenure with the current employer has a non-linear impact on the probability of receiving training. 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. The worker's employment status (whether s/he is a full timer (at least 35 hours weekly) or not, whether s/he is in a fixed contract), does not statistically impact on the probability of receiving training once we control for technological and organisational changes.

It has been noted before that whether the workplace operates in the broadly defined private sector or not is an important determinant of older workers' training (Wooden et al., 2001). This study also shows that the introduction of training schemes in the last two years does not increase the probability of older workers' training. We will return to this issue later, by discussing how technological change impacts upon the workplace's decision to introduce training schemes. Variables that capture the extent of competition the workplace faces produce mixed results. For example, Table 3 and Table 4 show that import competition increases the workers' chances of receiving training in both the full sample and in the sample of older workers (aged 45 and plus). The dummy variables for competition (intense, strong, moderate, some) relative to "limited competition" are negative and statistically significant in the full sample, but they do not significantly reduce training in a sample of older workers.

Specification IV adds variables that capture technological change. The results obtained using a sample of all workers and a sub-sample of older workers in Table 3 and Table 4, respectively, show interesting differences. For example, starting with variables that proxy for technological change at the workplace level, both tables show that the introduction of new machinery (*Workplace New Machinery=1*) has a negative impact on a worker's training in both Tables 3 and 4. Technological benchmarking (*Workplace Technology Benchmarking=1*) is positive and statistically significant in the full sample (Table 3), but non-statistically significant in Table 4. Technological change at the industry level as measured by the direct technology flow (7) has a negative impact on the probability of training in both samples, but it is statistically significant only in the sample of older workers. This result somehow contrasts with empirical evidence on the impact of technological change on training (e.g., Lillard and Tan, (1986)). Overall, the negative impact of technological change on older workers' training is consistent with Proposition 1. In the context of our analysis, it suggests that technological change may negatively impact on the workers' skill. Skill obsolescence in turn negatively impacts on the workplace decision to train its employees. Note that the obsolescence hypothesis could explain

[3] 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

why the negative effect of workplace technological change on training is somehow more intense in a sample of older workers.

Interestingly, Table 4 shows that the indirect technology flow variable IRY as expressed by (9), impacts positively on the chances for older workers to get training. As indicated in section three, this is consistent with the view according to which technological diffusion makes human capital less vintage-specific thus increasing the profitability of workers' training. Table 3 and Table 4 show that this effect is particularly strong in a sample of older workers, where the *IRflow* variable reaches statistical significance at the 5 percent level.

I now move to another measure of training reported in AWIRS 1995, namely whether a workplace has introduced a training scheme in the last two years.

6.1. Workplace training schemes, workforce age composition and technological change

Table 5 reports Probit estimation for the probability that a training scheme was introduced in the workplace in the last two years. The main hypothesis being tested is that, after controlling for a number of workplace and industry-specific characteristics that may induce an employer to provide training, workplaces with a larger percentage of older employees (aged 50 and plus) will be more reluctant to introduce training scheme.

This table reports three nested specifications. All of them include dummy variables for the 2-digit industry of belonging. Starting with Specification I, which includes only the percentage of older employees, a positive percentage of older workers (as opposed to none) appear to have a positive effect on the workplace chances of introducing training. Note that if the percentage of older workers is higher than 50 percent, this variable does not statistically significantly impact on the introduction of training schemes in the workplace. Going from Specification I to the full specification (Specification III), Table 5 shows that these results are not robust to the introduction of other control variables. For example, in the most complete specification (III) with proxy for technological change both at the industry and at the workplace levels, the percentage of older workers does not significantly affect the dependent variable.

Workplace technological change is in general positively correlated with the chances of introducing new training schemes. When technological change at the 2-digit industry level is among the control variables (Spec. III), we still find a positive impact of workplace technological change on workplace training. Note that in general, the positive correlation between workplace introduction of training schemes and workplace technological change contrast with the negative correlation found at the individual level. In specification III, industry technological change decreases the chances of workplace new training schemes.

6.2. Does technological change affect all older workers in the same way?

The model outlined in section three suggests that both technological innovation and diffusion, by impacting on the transferability of skill between consequent vintages of technology and across workplaces/industries, may affect workers' training differently depending on their age. A proper test of Propositions 3 and 4 require individual workers' panel data that inform us about the past and present levels of training the individual receives. Alternatively, and somehow ignoring possible cohort specific effects, we can run the same specifications for four distinct groups of workers, namely all workers, those aged 45 to 49, those aged 50 to 54 and those who are 55 or older. The results of such estimation are available upon request. Here suffice to summarise the findings as follows:

- Industry technology level (Rflow (7)) is *negatively* correlated with older workers' training. This is particularly true for workers aged 55 and plus.
- Our measure of technological diffusion (IRflow (9)) is *positively* correlated with older workers training (particularly those aged 55 and plus).
- The introduction of a training scheme at the workplace level in the last two years increases the probability of training for workers who are between 45 and 49, but it does not affect the probability of training for workers aged 50 and plus.

7. POLICY IMPLICATIONS

The model sketched in this study splits the technological change occurring at the industry level into two components: technological innovation, the direct investment in R&D by the industry, and technological diffusion, as measured by the R&D content of capital and intermediated goods imported from other domestic industries. This study tests the hypotheses according to which direct and indirect technological change has very different effects on the training opportunities that the workplace provides for older workers (aged 45 and above). The direct technological change measure has a negative effect on older workers' training; on the contrary, technological diffusion has a strong positive effect, particularly on the training opportunities of the age groups that appear particularly disadvantaged in the labour markets.

These findings have potentially significant policy implications. In the context of the theoretical framework proposed in section three (Proposition 1), the finding of a negative correlation between industry technological innovation and older workers' training could be due to obsolescence of workers' training. From a policy perspective, a result documenting that older individuals in industries undergoing technological change have lower training opportunities may suggest that these workers also have shorter working careers. In fact, from the model of Ben-Porath (1967) we learn that on-the-job training is positively correlated with the slope of the wage-age profile. The AWIRS may not be the most appropriate data set to check the robustness of this argument, mostly due to the way training is measured. However, a result pointing to a negative effect of industry technological change on older workers' training suggests that predictions regarding labour shortages in Australia may not be overly pessimistic.

This raised the attention on a number of important measures that can be taken to reduce such an effect. For example, to the extent that there are complementarities between general human capital (e.g., education) and training it would be advisable to prepare older cohorts of workers facing technological innovation in their workplace by investing in their education. Note that this is consistent with a very rich literature that points to education as enhancing the ability to deal with disequilibria (Schultz, T. 1975) and enlarging the set of employment opportunities outside the current work (Magnani, 2001). Other studies have pointed to the positive relationship between "outside options" and career opportunities of "marginal workers" in internal labour markets (e.g., Blackaby et al., 2005).

The finding that technological diffusion enhances the training opportunities available to older workers requires some specifications. First of all, this result is broadly consistent with the idea that technological diffusion reduces the technological distance between subsequent vintages of innovation, thus increasing the degree of workers' skill transferability across different generations of machines. Viewed in this light, this result is consistent and complementary to the one commented above, which instead resulted from technological innovation increasing skill obsolescence. Secondly, this result has industrial policy implications, the grounding of which requires a thorough understanding of what is measured by *IRflow* in (9).

Notoriously, technology is hard to measure. As clearly stated in Griliches (1979), the level of knowledge in any one sector of the economy not only derives 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. In measuring indirect technology we could adopt two well known approaches, namely the flow approach and the stock approach, to measure "own" and "indirect" technology. The perpetual inventory (stock) approach and the flow approach differ substantially in terms of the way technological distance is measured. It is possible to interpret the "indirect" technology measured by means of a flow approach as (9) as a proxy for "rent" spillovers across industries, while the stock approach measure of "indirect" technology is a better proxy of pure knowledge spillovers (see Griliches 1979, pp. 104). In fact, despite the relatively high sample correlation between the various US measures of own and indirect technology (e.g., Magnani, 2006) there is little doubt that the two set of technological measures are very different from each other. Rent spillovers occur in relation to actual transactions of intermediate and capital goods between firms/industries. Under competitive pressure, the suppliers of these goods are not able to raise prices proportionally to quality improvements in their products. As the quality/price ratio rises, firms/industries that use such goods benefit from R&D spillovers generating from the suppliers. On the contrary pure knowledge spillovers are more directly related to the knowledge embodied in the innovation.

Deriving policy implications from the result reported in this study is now easier. This finding points to the importance of technology spillovers that translate into a clear economic (cost reducing or quality enhancing) incentive. The creation of R&D network in which technological innovation is shared by means of flows of imported capital and intermediate goods would thus positively affect the training opportunities of older workers by impacting on the transferability of their skill across different vintages of capital.

8. CONCLUSION

This study has investigated the impact of technological and organisational change on older workers' training. The model sketched in this study critically addresses important empirical questions regarding how technological change shapes the labour market opportunities of older workers. The main results can be summarised as follows:

1. Age significantly affects training opportunities. This is so even after controlling for a large number of individual-specific, workplace-specific and industry-specific variables.

2. Technological change innovation significantly reduces older workers' training (aged 45 and plus). This result emerges by using a variety of measures of technological change, both at the workplace level (e.g., introduction of new machinery) and at the industry level (industry technology flow). When the sample of older workers (aged 45 and plus) is decomposed into subgroups by age, it appears that industry technological change particularly reduces the training opportunities of those workers belonging to the age group 55 and plus.

3. Technological diffusion increases the chances of older workers' training. This result is particularly strong in a sample of workers aged 55 and plus.

To conclude, because technological diffusion appears to have a strong and positive impact on older workers' training (particularly for those, aged 55 and plus, that the literature identifies as the most vulnerable group in the senior labour force) it is important to check the robustness of such results to different measures of technological diffusion. We leave this task to future research.

Table 1: Weighted (to the population) summary statistics (mean) for individual specific characteristics

Selected variables	Full sample	45-49	50-54	55 and plus
Training	0.67	0.69	0.64	0.54
On a Fixed Contract	0.10	0.10	0.06	0.07
Weekly Hours	36.00	37.00	37.00	36.00
Tenure	6.42	8.35	11.60	13.80

Table 2: Summary Statistics for direct R&D, indirect R&D and technology flows, 2-digit ANZSIC industries

Selected 2-digit manuf. industries	ANZSIC	direct R&D	indirect R&D	*Rflow*	*Irflow*
Coal mining	11	0	0.0045	0.00	1.32
Food, Beverages and Tobacco	21	0.0033	0.0028	1.19	0.90
Textile, Clothing, Footwear and Leather	22	0.0016	0.0022	0.40	0.69
Wood and Paper products	23	0.0016	0.0033	0.50	0.97
Printing, Publishing and Recorded Media	24	0.0036	0.0037	0.99	1.13
Petroleum, Coal, Chemical and Ass. Prod.	25	0.012	0.003	0.06	0.013
Non-metallic Mineral Product	26	0.008	0.002	3.38	0.75
Metal Product Manufacturing	27	0.009	0.005	0.03	0.01
Machinery and Equipment	28	0.046	0.005	0.16	0.015
General Construction	28	0	0.007	0.00	2.49
Communication Services	71	0	0.003	0.00	1.66
Financial Services	73	0	0.005	0.00	1.32

Table 3: Weighted[a] Probit Estimation of Training for All workers

Explanatory variables	Specific. I	Specific. II	Specif. III	Specif. IV
Individually-specific				
Male	-0.105***(0.036)	-0.081**(0.038)	-0.075*(0.040)	-0.027(0.044)
Age 50-54	-0.026(0.073)	-0.027(0.079)	-0.004(0.084)	-0.045(0.089)
Age 55 and plus	-0.22***(0.081)	-0.206**(0.086)	-0.226**(0.095)	-0.284***(0.101)
Tenure	-0.028***(0.0065)	-0.028***(0.0069)	-0.033***(0.0072)	-0.039***(0.008)
$Tenure^2$	0.0005**(0.0002)	0.0006**(0.0003)	0.0009***(0.0003)	0.001***(0.0003)
Full-timer (hours ≥ 35)	0.182***(0.043)	0.168***(0.045)	0.098*(0.050)	0.089(0.06)
Non-production	0.296***(0.044)	0.264***(0.047)	0.371***(0.053)	0.307***(0.060)
High School diploma	0.147***(0.047)	0.164***(0.050)	0.130***(0.050)	0.052(0.053)
Vocational training	0.029(0.049)	0.0526(0.052)	0.024(0.054)	-0.006(0.056)
Undergrad. Degree	0.203***(0.063)	0.273***(0.006)	0.264***(0.075)	0.266(0.086)
Diploma	0.178***(0.065)	0.292***(0.0698)	0.042(0.072)	0.059(0.08)
Postgraduate degree	0.070(0.064)	0.145**(0.0706)	0.278***(0.101)	0.261**(0.114)
Happy with hours of work	0.175***(0.036)	0.170***(0.038)	0.167***(0.042)	0.167***(0.045)
Fixed contract	-0.055(0.057)	-0.053(0.065)	0.155*(0.086)	0.145(0.095)
Workplace-specific				
Private sector		-0.066*(0.0345)	-0.17***(0.065)	-0.139*(0.041)
Size		-0.00004(0.00003)	0.00004(0.00006)	0.00003(0.00007)
Training program < 2 years		0.063*(0.033)	0.078**(0.037)	0.073*(0.040)
Market competition				
Import competition			0.136***(0.039)	0.163***(0.041)
Intense competition			-0.215***(0.079)	-0.216**(0.091)
Strong competition			-0.237***(0.080)	-0.244**(0.092)
Moderate competition			-0.196**(0.091)	-0.178*(0.105)
Some comepetition			-0.084(0.133)	-0.084(0.149)
Limited competition				
Technological change				
Workplace New Machinery?				-0.302***(0.053)
Workplace technology benchmarking?				0.119***(0.041)
Own technology *Rflow*				-0.39(0.027)
Indirect technology *IRflow*				0.24(0.030)
No. Observations	16898	15635	8019	6870
F-test	13.66***	11.52***	9.38***	8.68***

Notes: (a) Data are weighted to the population of employees at non-farm workplaces with 20 or more employees. (b) ***Significant at the 1% level. **Significant at the 5% level. *Significant at the 10% level.

Table 4: Weighted[a] Probit Estimation of Training for Older Workers (aged 45 and plus)

Explanatory variables	Specific. I	Specific. II	Specif. III	Specif. IV
Individually-specific				
Male	-0.182(0.715)	-0.125*(0.075)	0.028(0.0840)	0.050(0.096)
Age 50-54	-0.084(0.069)	-0.093(0.073)	-0.128(0.0843)	-0.189**(0.091)
Age 55 and plus	-0.273***(0.076)	-0.276***(0.080)	-0.348***(0.094)	-0.434***(0.103)
Tenure	-0.028***(0.010)	-0.029***(0.080)	-0.005(0.012)	-0.008(0.013)
Tenure^2	0.0006*(0.0003)	0.0007**(0.0003)	0.0001(0.0003)	0.0003(0.0004)
Full-timer (hours ≥ 35)	0.078(0.076)	0.019(0.080)	-0.182*(0.107)	-0.150(0.134)
Non-production	0.393***(0.076)	0.334***(0.080)	0.46***(0.103)	0.386***(0.116)
High School diploma	0.109(0.086)	0.144(0.091)	0.243**(0.104)	0.163(0.114)
Vocational training	-0.091(0.1)	-0.087(0.104)	-0.036(0.102)	-0.043(0.109)
Undergrad. Degree	0.114(0.117)	0.185(0.120)	0.442***(0.170)	0.348*(0.191)
Diploma	0.167(0.112)	0.211*(0.117)	0.164(0.154)	0.191(0.171)
Postgraduate degree	0.017(0.117)	0.184(0.131)	0.349*(0.198)	0.176(0.230)
Happy with hours of work	0.186***(0.065)	0.210***(0.069)	0.29***(0.087)	0.293***(0.094)
Fixed contract	-0.006(0.127)	0.017(0.138)	0.236(0.163)	0.057(0.184)
Workplace-specific				
Private sector		-0.20***(0.061)	-0.371***(0.122)	-0.194(0.139)
Size		-0.0001(0.00006)	-0.0001(0.0001)	0.00003(0.0001)
Training program < 2 years		0.067(0.060)	0.002(0.072)	0.033(0.078)
Market competition				
Import competition			0.232***(0.077)	0.279***(0.085)
Intense competition			-0.140(0.150)	-0.116(0.178)
Strong competition			-0.027(0.150)	-0.052(0.178)
Moderate competition			-0.279(0.175)	-0.136(0.210)
Some comepetition			0.054(0.250)	0.064(0.292)
Limited competition				
Technological change				
Workplace New Machinery?				-0.395***(0.103)
Workplace technology benchmarking?				0.068(0.080)
Own technology *Rflow*				-0.162***(0.053)
Indirect technology *IRflow*				0.154**(0.061)
No. Observations	4658	4288	1984	1690
F-test	7.98***	7.82***	5.38***	4.28***

Notes: (a) Data are weighted to the population of employees at non-farm workplaces with 20 or more employees.
(b) ***Significant at the 1% level. **Significant at the 5% level. *Significant at the 10% level.

Table 5: (Weighted) [a] probit estimation of the probability of introduction of a training scheme in the workplace in the last two years.

Explanatory variables(b)	Specif. I	Specif. II	Specif. III
Percent of employees aged 50 and +			
Dummy for 1% - 10%	0.142**(0.066)	0.121*(0.067)	0.085(0.083)
Dummy for 11% - 25%	0.221***(0.070)	0.190**(0.071)	0.113(0.088)
Dummy for 26% - 50%	0.216***(0.078)	0.198**(0.079)	0.184*(0.097)
Dummy for > 50%	0.128(0.168)	0.087(0.167)	0.198(0.178)
Workplace Technological change			
New office equipment		0.017(0.039)	-0.099**(0.047)
New machinery		0.132***(0.043)	0.15***(0.050)
Technology benchmarking		0.196***(0.027)	0.227***(0.0320)
Industry technology			
Own technology (Rflow)			-0.164***(0.040)
Indirect technology (IRflow)			-0.060(0.051)

Notes:

(a) Data are weighted to the population of workplaces with 20 or more employees.
(b) All specifications include dummy variables for the 2-digit industry of the workplace.
(c) ***Significant at the 1% level. **Significant at the 5% level. *Significant at the 10% level

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