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Vertical Disintegration and Training: Evidence from a Matched Employer-Employee Survey

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Abstract

A recent literature has argued in favour of a sizeable productivity enhancing effect of outsourcing. However, outsourcing implies the possibility of substituting away from internal labour services towards the employment of external workers in non-core activities of the firm. The effect of outsourcing on workers' training opportunities appears to be an empirical matter. Using a matched employer-employee survey for Australia and a range of econometric strategies that aim to control for selection on observables, I find robust evidence of large productivity enhancing-effects of outsourcing on workers' training, particularly for older workers.

1 Introduction.

Two major global phenomena are occurring under our eyes, namely the rapid dismantling of traditional internal labour market following the spread in the use of outsourcing and population ageing. Starting from the 1980s firms, particularly in the Western world, but not only, have started engaging in widespread organizational changes involving strategies as diverse as outsourcing and job redesign. Population ageing is profoundly changing the age profile of the population and the composition of the labour force in OECD countries. This paper is motivated by the recognition that there is widespread uncertainty over the impact of outsourcing on older workers. A recent literature has argued in favour of a sizeable productivity enhancing effect of outsourcing (for example by Harris, Siegel and Wright (2005), and more recently by Morrison-Paul and Yasar (2009) and Magnani and Prentice (2009)). However, outsourcing implies the possibility of substituting away from internal labour services towards the employment of external workers in non-core activities of the firm. The effect of outsourcing on workers' training opportunities appears to be an empirical matter. Given the importance of training for older workers' training opportunities, this research question is particularly important in the face of population ageing.

We adopt the usual, although broad, understanding of outsourcing as a process of turning over a part or all of those functions (or skills) that fall outside the organization's chosen core competencies to an external supplier, whose core competencies and skills are the functions being outsourced. So conceived, outsourcing may have no beneficial effects or even negative effects on workers' training opportunities (Drucker, 1995; Quinn and Hilmer, 1994). Substitutability between internal labour and externally hired labour services may imply that outsourcing threatens older workers' training opportunities, particularly in the face of skills obsolescence. If however outsourcing improves the productivity of internal labour, then this productivity effect may offset (wholly or partially) substitution effect of outsourcing on workers' training opportunities.

This paper addresses this gap in the literature. I employ the Australian Workplace Industrial Relations Survey (AWIRS) dataset, which is derived from a matched employer-employee survey uniquely designed to capture those technological and organizational changes that have been experienced by many economies in the Organization for Economic Co-operation and Development (OECD). I first present robust estimates of the impact of outsourcing on workers' training. I then investigate whether considerations of the possible endogeneity of organizational changes involving outsourcing confirm the findings of large productivity enhancing-effects of outsourcing, which can explain the positive impact of outsourcing on workers' training. In particular, I discuss and test a set of hypotheses concerning the observed relative disadvantage in training opportunities faced by older workers (aged 45+) when firms undergo rapid technological change and workplace restructuring.

One important finding of this study is that the increased use of outsourcing enhances the training opportunities of internal workers, particularly those of older workers. The economic significance of this impact is sizeable. After implementing Propensity Score Matching estimation of the effect of a rise in outsourcing on the treated workplaces and after including a wide range of individual-specific and workplace-specific characteristics, I find that the average treatment effect of an increase in outsourcing on older workers' training employed in the "treated" group of workplaces (ATT) is 8 percent. This result is consistent with the hypothesis that outsourcing impacts upon workers' training via a combination of factors, a *substitution-enhancing* effect and a *productivity-enhancing* effect of outsourcing. However it suggests that the latter effect dominates the former. Interestingly, the positive effect of outsourcing on workers' training appears to be stronger in technologically leading workplaces, those who benchmark against technology, as compared to less technologically dynamic workplaces.

Both of these results have important implications. Firstly, they suggest that outsourcing and workers' training are parts of an orchestrated strategy to optimize the use of human resources in the face of an increasingly technologically complex environment. Secondly a finding that both oursourcing and technology effects are stronger in workplaces that are technological leaders indicates the presence of complementarities between technology and organizational changes.

This study is organized as follows: section two reviews the existing literature on the determinants of outsourcing and its possible effects. In section three, I illustrate the nature of the Australian AWIRS-1995 dataset after introducing the econometric specification. Section four discusses the empirical results. Section five concludes.

2 Vertical disintegration and training: the role of input substitutability.

Outsourcing is a process in which a company purchases from outside firms goods and services which the company might otherwise have employed its own staff to produce. In other words, outsourcing is a case when a manufacturer pays a human resources firm to manage its payroll and benefits systems. In investigating the reasons behind the spread of contracting out (outsourcing) in OECD countries since the 1970s, the economic literature has focused on two main factors, namely the need to save on labour costs (the *labour-cost saving hypothesis*) and the *product-market volatility hypothesis* – the creation of dualistic labour markets in which the secondary component of the labour force is used as a buffer to protect the primary workers from the effect of product market volatility (e.g. Autor 2003, Abraham 1996, Abraham and Taylor 1996, Magnani 2006b). According to the *labour-cost saving hypothesis*, an increase in outsourcing could indicate a desire by the firm to save on labour costs, possibly by reducing its training expenses and thus reducing workers' training opportunities.

A third explanation for the spread of contracting out has recently emerged. The *technology standardization hypothesis* appeals to explanations such as special expertise possessed by the outside contractor and that are applicable to the hiring firm. For instance, Segal and Sullivan (1997) and Kahn (2000) suggest that, insofar as tasks requiring substantial investment in firm-specific skills are usually ill-suited to the use of temporary workers, technological standardization makes firm-specific knowledge less important and thus shifts upward the demand for outsourced labour services.

Recent empirical contributions to the literature on outsourcing (for example, Morrison-Paul and Yasar 2009) have also stressed that firms' productivity depends on their potential to minimize production costs by substituting among a variety of inputs. The presence of a *substitution-enhancing effect* of outsourcing, found for example by Harris, Siegel and Wright (2005) and more recently by Magnani and Prentice (2009), has important implications for our question. Clearly, if the presence of outsourcing is the result of the relatively easier substitutability between internal and external workers, the *substitution-enhancing effect* of outsourcing could *reduce* workers' training.

2.1 Vertical disintegration and training: the role of the productivity enhancing effect of outsourcing.

Recently, some studies have contributed to argue in favor of a *productivity-enhancing effect* of outsourcing. Siegel (1995) and ten Raa and Wolff (2001) have documented that the use of outsourced labour services greatly contributed to the productivity recovery in U.S. manufacturing in the late 1980s and 1990s, although Houseman (2007) raises important concern with this interpretation. Morrison-Paul and Yasar (2009) show that plants that outsource domestically (subcontract inputs) and internationally (import inputs) are larger, more productive, and have higher skilled labour and capital than the control (non-outsourcing) plants. Consistent with the predictions of Antras and Helpman (2004), there is also evidence of enhanced productivity from input outsourcing both domestically and internationally. Magnani and Prentice (2009) focus on the U.S. manufacturing sector from the early 1970s to the mid 1990s to find robust evidence that outsourcing has contributed to higher quasi-rents and higher labour productivity. To the extent that outsourcing involving large productivity gains it potentially boosts the training opportunities available to workers.

These arguments have a number of important implications for the econometric identification of the effect of outsourcing on workers' training: *(i)* to the extent that outsourcing is more than simply substitution of inputs to reduce the labour costs, the productivity enhancing effect may be strong and in fact prevail over the substitution enhancing effect, thus potentially lead to a *positive* impact of outsourcing on workers' training opportunities; *(ii)* if outsourcing comes only with a substitution enhancing effect between internal and external workers, outsourcing should *reduce* workers' training opportunities. Formally, the impact of outsourcing on training depends on two factors:

$$\frac{\partial Training}{\partial ooutsourcing} = \overbrace{\frac{\partial Training}{\partial substitution}\frac{\partial substituion}{\partial outsourcing}} + \overbrace{\frac{\partial Training}{\partial productivity}\frac{\partial productivity}{\partial ooutsourcing}} \quad (1)$$

While the first addendum in (1) is potentially negative, the second addendum is likely to be positive. The net effect of outsourcing is an empirical matter, which this paper aims to address.

2.2 Organizational change and older workers' training

Evidence in the literature suggests that both technological and organizational 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 survey 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. While it is well accepted that organizational developments such as reorganization 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. Even less explored is the impact of specific forms of organizational change towards the disintegration of the firm.

Two important stylized facts motivate the attention I devote to the link between outsourcing and older workers' training. 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. Although the nature of the dataset used in this paper does not allow for a direct testing of the hypothesis that the trends towards vertical disintegration and outsourcing have narrowed the gap between training opportunities of workers differentiated by age, this paper tests the hypothesis that indeed outsourcing may have contributed to older workers' training via its strong productivity enhancing effect.

3 Data and Econometric strategy.

To estimate the effect of technological change on older workers' training, I start by adopting a simple latent variable model where I estimate the probability of receiving employer-sponsored training in equilibrium, $\Pr(Training_{ht}=1)$.[1] In the reference period (usually a year), individual h might engage in workplace training ($Training_{ht}=1$), or might not ($Training_{ht}=0$). Thus:

$$Training_{hit} = \begin{pmatrix} 1 \text{ if} \\ T^*_{hit} \geq 0 \\ 0 \text{ otherwise} \end{pmatrix} \tag{2}$$

$$T^*_{hit} = A_1 X_{ht} + \alpha(Contr\_up_{hit}) + A_2 Z_{hit} + A_3 TC_{hit} + A_4 OC_{hit} + \epsilon_{hit} \tag{3}$$

Equation (2) typically captures a latent decision rule. Worker h will receive training if the benefits for both firm i and worker outweigh the costs. T^*_{hit} then captures the (unobservable) gains (benefits net of costs), which depend on a number of factors. X_{ht} is a vector of individual specific characteristics, Z_{hit} is a vector of

[1] 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.

characteristics of individual h's workplace i in time t, comprising control variables for firm size, whether the workplace operates in the private or in the public sector, the extent of competition in the domestic market (whether the workplace is competing with foreign firms in the domestic market, with dummy variables for intense, strong, moderate, some competition relative to limited competition, and the "propensity" to train as proxied by the number of employees who were trained in the last two years. The vectors TC_{hit}, and OC_{hit} are sets of workplace-specific and industry-specific variables (technology innovation and diffusion) that proxy for technological change and organizational change, respectively. If the use of outsourcing has increased, a dummy variable ($Contr\_up$) takes value 1, 0 otherwise. Dummy variables for the sector of employment are included in all specifications.

3.1 Outsourcing as an endogenous decision.

If outsourcing is not randomly distributed in a sample of workplace, a binary probit specification for the dichotomous indicator of treatment ($Contr\_up$) does not work, because the error term would be correlated with explanatory variable. We address the potential endogeneity issue in the training regression by estimating a bivariate latent variables model

$$\begin{aligned} Training_{hit} &= \begin{pmatrix} 1 \text{ if} \\ T^*_{hit} \geq 0 \\ 0 \text{ otherwise} \end{pmatrix} \qquad (4) \\ \text{where } T^*_{hit} &= A_1 X_{ht} + \alpha(Contr\_up_{hit}) + A_2 Z_{hit} + \\ & \quad A_3 TC_{hit} + A_4 OC_{hit} + \epsilon_{hit} \qquad (5) \end{aligned}$$

$$Contr\_up_{hit} = \begin{pmatrix} 1 \text{ if} \\ C^*_{hit} \geq 0 \\ 0 \text{ otherwise} \end{pmatrix} \qquad (6)$$

$$\text{where } C^*{}_{hit} = g(WP_{ht}, (Tech\ Inn_{jt}), (Tech\ Diff_{jt})) + \varepsilon_2 \qquad (7)$$

We assume that the error term in the training regression ϵ_{hit} can be decomposed in the sum of two terms, say $(\theta_{hit} + \varepsilon_1)$ where θ_{hit} is a i.i.d term that refers to the probability of training for individual h in workplace i at time t, while ε_1 is potentially correlated with the workplace-specific error component ε_2 in (7), $Corr(\varepsilon_1, \varepsilon_2) \lesseqgtr 0$.For example, specific workers'characteristics could determine sorting of workers into workplaces. Controlling for such a correlation between error terms may alleviate any potential bias derived from sorting of workers into workplaces. Alternatively, there could be some unobservable workplace-specific factors that determine both left-hand-side variables. The system ((4)-(7)) constitutes a recursive bivariate probit model. As in Magnani (2006a) we assume that outsourcing can be explained by relying on the following arguments:

(i) the labor cost saving hypothesis (Abraham, 1996), according to which firm outsource part of their internal operations and productions to save on labour costs;

(ii) the market volatility argument (Rebitzer and Taylor, 1991; Segal and Sullivan (1997), where changes in the boundaries of the firm respond to the need to shelter the core workforce from the effects of volatility in demand.

(iii) the technology hypothesis, according to which outsourcing becomes appealing only when the technology distance between firms, which depends on technology innovation and diffusion, is sufficiently small (Magnani, 2006a).

Consistently with these hypotheses, we regress the binary indicator ($Contr\_up$) for workplace h in time t on a vector ($WP_{ht}, Tech\ Inn, Tech\ Diff$), of workplace-specific characteristics (product market variability, downsizing, practice of using contractors in the face of increasing (decreasing) demand, demand growth, competition on price) and industry-specific measure of technology innovaton and diffusion, $Tech\ Inn$ and $Tech\ Diff$, which proxy for the technology conditions that make outsourcing possible, as argued in (iii) above. Table 4 illustrates the results.

3.1.1 Propensity Score Matching and the Average Treatment effect (of outsourcing) on the treated

Propensity score matching attempts to overcome the problem of the existence of a selection bias arising from a set of observable characteristics X. The computation of the average treatment effect (training) on the treated (D=1) (those workers who are in workplace who have intensified the use of outsourcing in the last two years) could be computed as

$$E(Y1 - Y0|D = 1) = E(Y1|D = 1) - E(Y0|D = 1)$$

Obviously to carry out this computation we need to construct the counterfactual E(Y0 | D=1) – the outcome participants would have experienced, on average, had they not participated. The application of propensity score matching (PSM) allows us to "construct" the counterfactual and address the following question: what is the effect of a rise in outsourcing on training in observationally "equivalent" workplaces that only randomly select into the groups of "treated" and "non-treated" workplaces?

As clearly expressed in Siamesi (2001) the matching method relies on two main assumptions: *(i)* we assume that all relevant differences between the group workplaces that undergo vertical disintegration and the group of workplaces that does not, are captured by a set of observable characteristics Δ, such that the Conditional Independence Assumption (CIA) holds (Y0 is independent from D conditional on $p(x)$, where $p(x) \equiv \Pr(D = 1|\Delta = x)$; *(ii)* we select from the "non-treated" group of workers a control group in which the distribution of the estimated propensity to vertical disintegrate is as similar as possible to the distribution of such propensity in the "treated" group (the common support assumption).

To find a matching-pair for each recipient unit, we consider the two groups of treated and control workplaces in the region of common support of the propensity score, and then we construct a weighted average of the outcomes of more non-treated workers where the weight given to non-treated worker j is in proportion to the closeness of the estimated propensity score of h and j (Kernel matching).

Operationally, I compute propensity scores $p(x) \equiv \Pr(D = 1|X = x)$ by estimating the probability of $(Contr\_up)$ as function of a large set of factors such as workplace size, the non profit nature of the workplace, whether it competes on price, the intensity of the domestic market compentition, whether the product demand is seasonal, whether sales are trending upward, whether the workplace is downsizing, whether workplace aims to reduce labour costs or operative costs. Other variables that capture the technological reasons for outsourcing are the introduction of new office technology, new machinery, whether the workplace benchmarks in technology, whether there is an ongoing organizational change possibly involving task restructuring.[2]

3.2 The Data.

I use the data described in Magnani (2006a), which the interest reader may refer for further details. Here, it is sufficient to say that the 1995 Australian Workplace Industrial Relations Survey (AWIRS-1995) is a matched employer–employee survey that was conducted by the Australian 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 across 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 5 employment-size bands and 18 industry groups, thus providing 90 strata. For each workplace we use the appropriate weights so to make the sample of workplaces representative of the corresponding Australian population. 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, which is well representative of the 3.6 million people working in medium to large establishments (the response rate is 64%). It is important to stress that due

[2] We estimate a large number of specifications for ($Contr\_up$). In the selection of the specification we use to compute the ATT of ($Contr\_up$) on workers' training we are bound to satisfy the common support requirement and the balancing property requirement (see Ichino, 2002).

to sampling design, employees are not made representative of the workplace itself.

The AWIRS dataset contains a number of measures of training activity. In particular, the 1995 employee questionnaire asks the following question: *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% of employees answered "no" to this question, about 60% answered "yes" and the answer is missing for only 2% of the sample of employees.[3] The AWIRS dataset is organized in several different questionnaires, one of which is answered by a random sample of employees. The richness of the dataset allows for the control of a rather large number of employee characteristics that may impact upon training opportunities, such as age (15 and plus), gender, country of birth, the number of dependents and other family members individual h may be caring for, a quadratic variable for tenure at the current workplace, hours of work per week, a dummy variable for a fixed contract, dummy variables for education (highest degree achieved), occupation and job title. We exclude from the sample those individuals affected by any disability.

Furthermore, the AWIRS dataset allows for a control of a number of factors that may affect the workplace's decision regarding training, namely firm size, whether the workplace operates in the private or in the public sector, the extent of competition in the domestic market (i.e. whether the workplace is competing with foreign firms in the domestic market, represented by dummy variables for *Intense, Strong, Moderate,* or *Some* competition relative to *Limited competition*), and the "propensity" to train as proxied by the number of employees who were trainees last year.

3.2.1 Information on outsourcing and on changes in workplace organization.

The AWIRS dataset has been specifically designed to investigate the effect of organizational and market changes on workplace performance. In particular, I use survey questions related to "the introduction of major reorganization of workplace structure (for example, changing the number of management levels, restructuring

[3] Caveats and limitations of this measure of training are discussed in Magnani (2006a).

whole divisions, restructuring sections, and so on)" to construct a dummy variable for organizational restructuring (*Organ. restructuring=0,1*), which takes value 1 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)" leads to the dummy variable *Task restructuring* taking a value of 1, and 0 otherwise. Some of the variables asked at the managerial level can be directly related to the use of alternative employment arrangements, such as the increased use of casual employment arrangements (*Casual workers up*) and the increased use of contractors (*Contr_up=0, 1).*

3.2.2 Measuring technology change.

I refer to Magnani (2006a) for details on the workplace specific questions on technological change introduced in the last two years. In particular, the following questions and variables are particularly useful:

1. Introduction of major new office technology (*New office technology*)

2. Introduction of new plant, machinery or equipment (*New machinery*)

3. Does this workplace engage in technological benchmarking (*Tech. Benchmarking*)?[4]

From these survey questions, I construct dummy variables that take value 1 if the answer to the respective questions was positive, and 0 otherwise.[5]

The measures of industry-specific technological innovation and diffusion for industry j at time t are those already used in Magnani (2006a) and Magnani (2006b):

$$Tech.\ innovation_{jt} = \sum_{\tau} \left[\frac{R\&D\ \text{expenditure}_{j,t-\tau}}{Output_{j,t-\tau}} \right] \tag{8}$$

[4]The relevant question is:

In which of these categories (including technology), does this workplace benchmark?

[5]Magnani (2006a) and Blau and Shvydko (2007) discuss identification issues arising from the potential endogeneity of explanatory technology variables *at the workplace level.*

$$Tech.\ diffusion_{jt} = \sum_{\tau} \left[\frac{IndirR\&D1_{j,t-\tau}}{Output_{j,t-\tau}} \right] \quad (9)$$

See Appendix for details. Magnani (2006a) finds evidence of a differential effects of technology innovation and technology diffusion of workers' training. While technological innovation has a negative effect on older workers' training, confirming the hypothesis that innovation may induce skill obsolescence, particularly in older workers, technological diffusion usually has a positive effect, which is possibly the combination of two different effects of diffusion. Technology diffusion may shortens the distance between subsequent vintages of machines (thus reducing skill obsolescence), *and* enhance the substitutability of workers with those who are outside the firm's boundaries thus increasing outsourcing (Magnani, 2006b). These results also raise questions abour the impact of outsourcing, on workers' training. In particular, outsourcing will have a positive effect if the *productivity-enhancing effect* of outsourcing is greater than its *substitution-enhancing effect.*

Tables 1a reports summary statistics at the worker level. Table 1b reports the summary statistics of technological change and organizational change variables in Australian workplaces, AWIRS-1999.

4 The empirical results. Does outsourcing reduce training?

The Weighted-to-the-population summary statistics reported in Table 1a confirm that workers aged 50+ receive less training than younger workers. Table 1a does provide some evidence that older workers are employed in workplaces where workplace technology innovation and organizational change are prevalent.

Table 2 reports the marginal impact of a selected set of explanatory variables on the probability of training estimated by means of a probit model (full sets of results are available upon request). Two main results need to be emphasized. Table 2 confirms the finding according to which workers aged 55 and over appear disadvantaged in their chances of receiving training relative to the age group 25-29.[6] Workers aged 55 and over are almost 6.6% less likely to receive training than the reference age group 25–29 (left-hand side panel) and 10% less likely to received training compared to the age group 45–49 (central panel in Table 2).[7] Furthermore, Table 2 shows that the increased use of outsourcing in general impacts favourably on older workers' chances of training (workers aged 55+). Finally, controlling for technological change at the industry level appears to magnify this positive effect, as shown in Specification II and Specification III, in the central and bottom panels of Table 2, respectively. These results are consistent with the hypothesis of a positive net effect of outsourcing on training possibly due to a strong productivity enhancing effect of vertical disintegration found in other studies (e.g., Magnani and Prentice, 2009).

4.1 Technology, outsourcing and workers' training. Robustness exercises.

We test the robustness of our findings in three different ways. First, we would expect that if outsourcing has a positive effect on productivity this effect is larger in

[6]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 provided training from 0.64 to 0.54 and the reduction is statistically significant at the 99% level. A worker's general skill is important in determining the training result. In fact, the probability of being trained changes according to the occupation held by the employee. For example, employment 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 supports the idea of training/education complementarities.

[7]The results related to the workplace technology variables are consistent with those already reported in Magnani (2006a). When industry level measures of technological change, namely *Tech. innovation* and *Tech. diffusion* enter the probit estimation of training probability for workers aged 55 and over instead of the variables measured at the workplace level (central panel of Table 2), they both significantly impact upon workers' training and they do so in the expected way. It is also noteworthy that the size of the coefficients of the industry level technological change (*Tech. innovation*) increases significantly as we move from the older (aged 45+) to the oldest (aged 55+), a result that is consistent with a positive correlation between age and a skill obsolescence effect of technological innovation.

workplaces that are actively engaging with technology change, a main determinant of total factor productivity. Secondly, endogeneity issues may bias the results. If there are unobserved factors that impact positively on both outsourcing and training, failure to control for them may produce statistically significant coefficients for outsourcing even when its "true" impact is not so.

4.1.1 Outsourcing in technologically leading workplaces.

Table 3 illustrates the effect of technological change and outsourcing in two different sets of samples, namely workers employed in technologically leading workplaces, those that answer positively to the question: "Does this workplace engage in technological benchmarking (*Tech. benchmarking*)?". The top panel illustrates the marginal effects on the probability of training in workplaces for which *Tech. benchmarking=1.*

Two important sets of results emerge from comparing the top and bottom panels of Table 3. Firstly, the disadvantage faced by workers aged 55 and over compared to workers aged 25–29 (first column) and those aged 45–49 (second column) is statistically significant only in workplaces that engage in technological benchmarking (top panel). In these workplaces, older workers have training opportunities that are 15% and 26% lower than the base age group 25–29 and 45–49, respectively. In technologically leading workplaces *Tech. Innovation* reduces the training opportunities of older workers. Table 3 confirms that technology diffusion has, in general, a positive impact on training in both types of workplaces.This set of findings confirms the skill-obsolescence hypothesis of technological innovation.

A second set of findings emerges from a comparison of the effect of a spread of outsourcing in workplaces that engage differently with technological benchmarking (*Tech. benchmarking=0,1.* Vertical disintegration of the workplace, as indicated by dummy variables for an increase in outsourcing, does significantly alter the chances of workers' training in both types of workplaces, although this positive effect appears to be larger in samples of workers who are employed in workplaces that are technological leaders. Again, a disaggregation by age reveals that an increase in the extent of outsourcing increases older workers' training more than training for younger workers, and this is particularly so if employment is in workplaces for which *Tech. benchmarking=1.* Interestingly, these results are robust to the inclusion of a large set of variables measuring the extent of competition in the product market, and other variables that measure organizational change at the workplace level.

While none of these results allow us to exclude the existence of a substitution effect of outsourcing, all these results support the hypothesis that a productivity enhancing effect of outsourcing prevails over the substitutability effect between internal and "external" labour services.

4.2 Allowing for the endogeneity of outsourcing.

While the aim of this article is not to test the validity of any of the three possible arguments formulated to explain the spread of outsourcing, it is important that the results reported in the bottom panels of Table 4a (workers aged 15+) and in Table 4b (workers aged 45+) are broadly consistent with the arguments the literature has formulated to explain the propensity for a workplace to increase the use of contractors ($Contr\_up = 1$). For example, business cycle and product market volatility reduce the use of outsourcing, while product market trends tend to push towards workplace disintegration. Also, technology innovation at the industry level pushed towards vertical disintegration particularly in workplaces that do not benchmark against technology, possibly because of their need to attract outside skills. Interestingly, the practice of a workplace to compete on price is negatively correlated with the probability of outsourcing, a finding that, consistently with what Abraham and Taylor (1996) finds, confirms that outsourcing is not easily explained by the need to cut on labour costs.

Table 4a and Table 4b show that the estimate of ρ is around -0.30 in the full sample of workers of any age, and around (-0.52) in the sample of workers aged 45+. Both these correlation coefficients are statistically significant. Although selection of low-skill workers into workplaces that have a higher propensity to outsource may be explain the negative value of ρ, a significantly larger value of ρ for older workers, suggest that, this selection, if exists, is stronger for older workers. While the level of statistical significance varies considerably across samples, the Wald tests of the hypothesis that ρ equals zero allows us to reject at the 10 percent levels at least in the main samples. Since ρ measures the correlation between the outcomes after the influence of all controls is accounted for, a finding that ($Contr\_up$) significantly impacts on the probability of training is an important results.

Table 4a and Table 4b allow us to stress a number of interesting results:

(i) Controlling for the potential correlation between error terms in (5) and (7) makes the coefficients of ($Contr\_up$) much larger than in models in which outsourcing is assumed exogenous (e.g., Table 2 and Table 3).

(ii) When a full sample of workers is considered (Table 4a), the dummy variable for age 55+ is not statistically significant. This could be the effect of using an econometric specification that takes into account the possible correlation between workplace characteristics and workers' characteristics. However, workers aged 55+ are still strongly disadvantaged in their training opportunities relative to those aged 45-49 in samples of workers 45+ (Table 4b) if they are employed in technologically leading workplaces.

(iii) Consistently with the results reported in Table 3, the effect of the spread of outsourcing on workers' training (15+) is larger in technologically leading workplaces than in other workplaces (see Table 4a).

(iv) Workers aged 45+ seem to derive no training-related benefit from outsourcing if they are employed in technologically leading workplaces, but they do if they are in workplaces that do not benchmark against technology (see Table 4b).

Table 4c illustrates that the marginal effect of a change from ($Contr\_up = 0$) to ($Contr\_up = 1$) on the probability of training. We compute marginal effects as the difference between two conditional probabilities, specifically $P(training = 1|(Contr\_up = 1)$ and $P(training = 1|(Contr\_up = 0)$ (Greene, 2008) for specific samples of workers. Table 4c shows that this marginal effect is sizeable in both the full sample and the sample of workers aged 45 and plus A disaggregation of workers by skill levels (production workers/non-production workers) reveals that the marginal effect of outsourcing is much higher in samples of non-production workers, whatever is the age group considered.

4.3 An application of propensity score matching to estimate the ATT of outsourcing

Table 5 reports the Average Treatment effect on the Treated (ATT) computed by means of the Kernel-based method of matching, which associates to the outcome $training = 0, 1$ of "treated" individual h (those employed in workplaces that saw an increase in outsourcing) a matched outcome given by a kernel-weighted average of the outcomes of all non-treated individuals, where the weights given to non-treated worker j is in proportion to the closeness in propensity score between h and j. Table 5 reports a positive and statistically significant effect of $Contr\_up = 1$ on the probability of training when we consider a sample of workers aged 45 and plus in the region of common support (e.g., [0.00062; 0.4836] for older workers –see Figure 5a), compared to a positive, but non-statistically significant impact of outsourcing on the training chances in a sample of workers aged 15 and plus. The economic significance of these results are non-negligeable: propensity score matching ATT estimation reveals that an increase in outsourcing increases the probability of training for older workers' training by 8 percent.

4.4 Some caveats in the interpretation of results.

In many OECD countries, including Australia, workers who are still in the labour force at the ages of 55 and over may not be randomly selected from the corresponding age-specific population. This raises a selectivity problem that can make difficult it to extrapolate some results from samples to populations. Although this dataset does not allow me to specifically address this selectivity issue, it is important to give a sense of the potential bias contained in the estimated training probabilities for older workers. Figure 1 below clearly establishes a well know stylized fact, namely the gradual but consistent decline in labour force participation way before retirement age. Qualitative evidence recently collected to examine employment patterns for those aged from 50 and above indicates that people with better qualifications are more likely to be at work (Irving, Steels and Hall 2005, page 18). This is important as qualification is also positively correlated with the probability of training. Both these facts suggest that the relative training disadvantages faced by older workers vis-a-vis younger workers may indeed underestimate the effects of age and technology change on the full population of older workers. This is a relevant caveat that the reader must keep in mind when evaluating these results.

Here Figure 1.

A second important caveat originates from the use of a cross section dataset when in fact it would be preferable to use longitudinal data. To my knowledge it is difficult to combine the richness in measures of technology and organizational change at the industry and workplace level with longitudinal information on individual workers. The results reported in this study have been the subject of many robustness checks by means of the nested inclusion of controls for individual-specific characteristics, workplace characteristics, market characteristics, competition measures and subgroups of the above. The matched employer–employee data used in this study is sufficiently rich in details on the match between employers and employees to make me confident that these results are not driven by individual heterogeneity.

Finally, although this study is unable to accurately test for hypotheses concerning *time changes* in the training gaps existing between younger and older workers, the findings of this study suggest that the trend towards increasing outsourcing observed in the last few decades may help 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).

5 Final remarks and conclusions.

This study has investigated the impact of outsourcing on workers' training, with an emphasis on older workers'. Outsourcing may impact on training via two different effects. First, a workplace might use external workers because it can find outside what previously was only available within its boundaries (the *substitution-enhancing effect* of outsourcing). In other words, the availability of external skill that is potentially substitutable to internal skill may reduce the need for training. A second channel through which outsourcing may impact upon workers' training is its effect on workers' productivity. If there is substitutability between internal and external workers and, in the absence of any *productivity-enhancing effect* of outsourcing, we should expect a *negative* impact of outsourcing on workers' training.

We adopt a variety of econometric strategies, all involving a large number of individual-specific and workplace-specific controls derived from a matched employer-employee survey, to test the hypothesis of a significant productivity-enhancing effect of outsourcing. After controlling for the technological determinats of outsourcing, which may have an independent impact on training as shown in Magnani (2006b), this study has found robust evidence that an expanded use of outsourced labour services increases workers' training opportunities, although this result is significantly stronger in technologically leading workplaces and in samples of skilled workers (non-production). The economic significance of the impact of outsourcing on older workers (aged 45+)'s training is sizeable. After controlling for the potential selection on observables by means of Propensity Score Matching techniques and after including a wide range of individual-specific and workplace-specific characteristics, I find that, in the region of common support, an increase in outsourcing increases the probability of training for older workers' training by 8 percent.

Appendix.

I rely on industry-specific R&D expenditures to construct the measures of technological change at the industry level (subscript j) at time t (1995) (4) and (5) reported below:

$$Tech.\ innovation_{jt} = \sum_{\tau} \left[\frac{R\&D \text{ expenditure}_{j,t-\tau}}{Output_{j,t-\tau}} \right]$$

To measure technology diffusion we rely on the conceptual framework offered by Griliches (1979), who argues that 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. According to the flow approach, 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 $IndirR\&D1_{jt} = R\&D\_INT_{jt} + R\&D\_CAP_{jt}$ where $R\&D\_INT_{jt}$ is the R&D intensity embodied in intermediate goods and $R\&D\_CAP_{jt}$ is the R&D intensity embodied in capital goods that flow to industry j at time t. The technology diffusion measure becomes:

$$Tech.\ diffusion_{jt} = \sum_{\tau} \left[\frac{IndirR\&D1_{j,t-\tau}}{Output_{j,t-\tau}} \right]$$

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 $R\&D(direct)_{j,t}$, $IndirR\&D1_{j,t}$, $Tech.\ innovation$ and $Tech.diffusion$, respectively, for selected Australian manufacturing industries, as classified by 2-digit Australian New Zealand Standard Industrial Classification (ANZSIC) codes. Valadkhani (2005) provides a concordance table to match the International Standard Industrial Classification of All Economic Activities (ISIC) codes used by the OECD STAN/ANBERD dataset and the ANZSIC codes used in AWIRS.

References

Abraham, K.G. (1996) Restructuring the Employment Relationship: The Growth of Market Mediated Work Arrangements. In Abraham K. and McKersie, R. (eds) *New Development in the Labor Market: Toward a New Institutional Paradigm,* Cambridge, Mass.: Massachussets Institute of Technology Press, 85-119.

Abraham, K.G. and Taylor, S.K. (1996) Firms' Use of Outside Contractors: Theory and Evidence. *Journal of Labor Economics,* 13(3), 394-424.

Aubert, P., Caroli, E., and Roger, M. (2006) "New Technologies, Organization and Age: Firm Level Evidence," *The Economic Journal* 116 (February): F73–F93.

Antras, Pol & Helpman, Elhanan, 2007. "Contractual Frictions and Global Sourcing," CEPR Discussion Papers 6033, C.E.P.R. Discussion Papers.

Autor, D.H. (2003) Outsourcing at Will: Unjust Dismissal Doctrine and the Growth of Temporary Help Employment. *Journal of Labor Economics*, 21(1), January 2003, 1-42

AWIRS (1997) *Technical Report,* Department of Workplace Relations and Small Business, Canberra.

Bassanini, A., and Ok (2006), "How do firms' and individuals' incentive to invest in human capital vary across groups?" European Commission Directorate General Employment, Social Affairs and Equal Opportunities, February

Beckmann, M. (2004) "Age-Biased Technological and Organizational Change: Firm-Level Evidence and Management Implications," University of Munich.

Borghans, L. and ter Weel, B. (2006) "The Division of Labour, Worker Organization and Technological Change," *The Economic Journal* 116 (February): F45–72.

Blau, D.M. and Shvydko, T. (2007) *Labor Market Rigidities and the Employment Behavior of Older Workers*, IZA Discussion Paper No. 2996*,* August.

de Grip, A., (2006), "Evaluating human capital obsolescence" Research Centre for Education and the Labour Market, European Commission, OECD (February)

Greene, W. H., (2008), *Econometric Analysis,* Sixth Edition, Pearson International Edition, Pearson Prentice Hall.

Griliches, Z. (1979) "Issues in Assessing the Contribution of Research and Development to Productivity Growth," *The Bell Journal of Economics* 10 (1): 92–116.

Harris, R., Siegel D., and M. Wright, (2005) "Assessing the Impact of Management Buyouts on Economic Efficiency: Plant-Level Evidence from the United Kingdom," The Review of Economics and Statistics, Vol. 87, No.1, February, 2005, pp. 148-153.

Houseman, S., "Outsourcing, Offshoring, and Productivity Measurement in U.S. Manufacturing", Upjohn Institute Staff Working Paper No. 06-130, W. E. Upjohn Institute for Employment Research, April 2007

Kahn, S. "The Bottom-Line Impact of Temporary Work on Companies' Profitability and Productivity," in Francoise, C., Ferber, M.A., Golden, L. and Herzenberg, S.A. (eds) (2000) *Nonstandard Work: The Nature and Challenges of Emerging Employment Arrangements,* Industrial Relations Research Association, New York: 235–266.

Irving P., Steels J., and N., Hall, (2005), "Factors affecting the labour market participation of older workers: qualitative research". Department for Work and Pensions Research Report No 281, Department of Work and Pension, Leeds, HMSO

Lindbeck, A. and Snower, D. (2001) "Centralized Bargaining and Reorganized Work: Are they Compatible?" *European Economic Review* 45: 1851-1875.

Magnani, E. (2006a) "Technological Diffusion, the Diffusion of Skill and the Growth of Outsourcing in US manufacturing," *The Economics of Innovation and New Technology*, 2006, 15 (7, October): 617–647.

Magnani, E. (2006b) "Technological Change and Older Workers' Training," *International Journal of Economic Policy Studies* 1 (October): 45–69.

Magnani, E. and Prentice, D. (2009) "Outsourcing and Unionization: A Tale of Misallocated (Resistance) Resources," *Economic Inquiry,* forthcoming.

Morrison-Paul, C. and Yasar, M. (2009) "Outsourcing, Productivity and Input Composition at the Plant Level," *Canadian Journal of Economics* 42 (2, May) 422–

439.

Organization for Economic Co-operation and Development (OECD) (1998) "Work force ageing in OECD countries," in *The OECD Employment Outlook*, OECD Paris, June: 123–151.

Organization for Economic Co-operation and Development (OECD) (1997) *Technology and Industrial Performance. Technology Diffusion, Productivity, Employment and Skill and International Competitiveness,* OECD Paris.

Segal, L.M. and Sullivan, D.G. (1997) "The Growth of Temporary Services Work," *Journal of Economic Perspectives* 11(2): 117-136.

Sianesi, B., (2001) "Propensity score matching," United Kingdom Stata Users' Group Meetings 2001 12, Stata Users Group, revised 23 Aug 2001.

Siegel, D. (1995) "Errors of Measurement and the Recent Acceleration in Manufacturing Productivity Growth," *Journal of Productivity Analysis* 6: 297-320.

Ten Raa, T. and Wolff, E. N. (2001) "Outsourcing of Services and the Productivity Recovery in US Manufacturing in the 1980s and 1990s," *Journal of Productivity Analysis* 16.

Valadkhani, A. (2005) "Which Industries Create More Employment? A Cross-Country Analysis," Working Paper No. wp05-07, School of Economics, University of Wollongong, May, accessed at http://ideas.repec.org/p/uow/depec1/wp05-07.html.

Table 1a: Weighted means of workers' characteristics by age groups.

	Full sample	Workers aged 45-49	Workers aged 50-54	Workers aged 55+
Employer-provided training	0.67	0.69	0.64	0.54
New office technology	0.13	0.13	0.11	0.10
New Machinery	0.13	0.13	0.17	0.18
Industry technology change				
Tech Innovation*	0.24 (0.01)	0.23 (0.02)	0.30 (0.03)	0.26 (0.03)
Tech Diffusion*	0.85 (0.01)	0.81 (0.03)	0.78 (0.03)	0.72 (0.03)
Organizational Change				
Organizational restructuring	0.43	0.44	0.40	0.38
Task restructuring	0.21	0.20	0.22	0.26
Casual workers up	0.17	0.16	0.17	0.15
Contractors up	0.04	0.05	0.03	0.05
Intensity of Market Competition				
Intense competition	0.39	0.37	0.39	0.36
Strong competition	0.33	0.30	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

Note: *: continuous variable, standard deviation in parentheses

Table 1b: Summary statistics of technological change and organizational change variables in Australian workplaces, AWIRS-1999

Introduction of new office technology	48.7
Introduction of new machinery	30.7
Workplace benchmarking in technology	88.6
Workplace engaged in organizational restructuring	54.4
Workplace engaged in task restructuring	45.2
Workplace increased its use of contractors	5.44
Workplace increased its use of casual workers	17.5

Table 2: Weighted[(a)] estimation of marginal effects for the probability of training: Sample of all workers, workers aged 45+ and workers aged 55+. Robust[(b)] standard errors in parentheses.

	All workers[(d)]		***Workers 45+***		***Workers 55+***	
			Specification I[(c)]			
Age 45-49	0.020	(0.026)	----	----	----	----
Age 50-54	0.009	(0.033)	-0.011	(0.033)	----	----
Age 55+	-0.066**	(0.037)	-0.101**	(0.039)	----	----
New off. Tec	0.095**	(0.031)	0.047	(0.055)	-0.074	(0.118)
New mach.	-0.013	(0.033)	-0.028	(0.055)	-0.093	(0.117)
Tec. Bench	0.022	(0.019)	0.0008	(0.030)	-0.035	(0.065)
Contractors up	0.020	(0.020)	0.044	(0.035)	0.133*	(0.074)
Observations	7271		1664		380	
Log-likelihood	-4716.4		-1124.5		-957.3	
			Specification II[(c)]			
Age 45-49	0.028	(0.028	----	----	----	----
Age 50-54	0.012	(0.035)	-0.016	(0.036)	----	----
Age 55+	-0.068*	(0.040)	-0.111**	(0.041)	----	----
Tec. Innovation	-0.019	(0.013)	-0.053**	(0.022)	-0.099**	(0.046)
Tec. Diffusion	0.008	(0.015)	0.027	(0.025)	0.159**	(0.057)
Contractors up	0.047**	(0.022)	0.079**	(0.038)	0.232**	(0.076)
Observations	6224		1416		322	
Log-likelihood	-4062.8		-959.7		-207.7	
			Specification III[(c)]			
Age 45-49	0.032	(0.028)	----	----	----	----
Age 50-54	0.012	(0.036)	-0.017	(0.035)	----	----
Age 55+	-0.063	(0.040)	-0.113**	(0.041)	----	----
New off. Tec	0.112**	(0.035)	0.026	(0.063)	-0.089	(0.130)
New mach.	0.012	(0.036)	-0.051	(0.060)	-0.140	(0.124)
Tec. Bench	0.025	(0.021)	0.014	(0.033)	-0.058	(0.071)
Tec. Innovation	-0.014	(0.013)	-0.049**	(0.022)	-0.094**	(0.046)
Tec. Diffusion	0.007	(0.015)	0.026	(0.025)	0.156**	(0.057)
Contractors up	0.043*	(0.022)	0.075*	(0.038)	0.235**	(0.077)
Observations	6224		1416		322	
Log-likelihood	-4042.1		-957.3		-205.6	

Notes:

(a) Data are weighted to the population of employees at non-farm workplaces with 20 or more employees.

(b) Standard Errors are adjusted for clusters in workplace identifier.

(c) All specifications include a set of *individual specific variables* (dummy variables for age ranges between 15 to 55plus, a quadratic polynomial in tenure, five dummy variables for educational attainment, a dummy variable for fixed contract employment, a dummy variable for full time job, a dummy variable for non-production job); a set of *workplace-specific attributes* (private sector, workplace size, whether this workplace has engaged with training in the last two years); a set of *product market attributes* (private sector, whether competing with foreign firms, a set of dummy variables for domestic competition); a set of variables capturing the nature of *workplace organizational change* (Organisational Restructuring=0,1), (Task Restructuring=0,1); dummy variables for broad industrial sectors.

(d) The age range 25-29 is the omitted age dummy variable.

Table 3: Weighted[(a)] estimation of marginal effects for the probability of training: Sample of all workers, workers aged 45+ and workers aged 55+, Workplaces that do (not) benchmark in technology in top (bottom) panel. Robust[(b)] standard errors in parentheses.

Selected expl.vars.	***All workers***[(c), (d)]		***Workers 45+***		***Workers 55+***	
			Workplace technology benchmarking =1			
Age 45-49	0.063	(0.037)	----	----	----	----
Age 50-54	-0.020	(0.050)	-0.079	(0.052)	----	----
Age 55+	-0.150**	(0.063)	-0.255***	(0.064)	----	----
New off. Tec	0.104*	(0.056)	0.022	(0.096)	0.199	(0.254)
New mach.	0.006	(0.055)	-0.089	(0.095)	-0.321	(0.205)
Tec. Innovation	-0.017	(0.020)	-0.071**	(0.033)	-0.213**	(0.100)
Tec. Diffusion	-0.021	(0.027)	0.018	(0.042	0.183*	(0.104)
Contractors up	0.052*	(0.026)	0.015	(0.057)	0.310**	(0.123)
Contr.* age55+	0.150*	(0.073)	0.187*	(0.087)	----	----
Observations	2678		642		154	
Log-likelihood	-1627.2		-392.5		-75.3	
			Workplace technology benchmarking =0			
Age 45-49	0.013	(0.028)	----	----	----	----
Age 50-54	0.046	(0.036)	0.032	(0.035)	----	----
Age 55+	-0.017	(0.040)	-0.020	(0.041)	----	----
New off. Tec	0.133**	(0.042)	0.046	(0.063)	-0.251	(0.152)
New mach.	-0.004	(0.050)	-0.094	(0.079)	-0.080	(0.149)
Tec. Innovation	-0.014	(0.017)	-0.047	(0.031)	-0.096	(0.068)
Tec. Diffusion	0.023	(0.019)	0.024	(0.032)	0.150**	(0.073)
Contractors up	0.027	(0.030)	0.097*	(0.056)	0.264**	(0.098)
Contr.* age55+	-0.013	(0.098)	-0.054	(0.116)	----	----
Observations	3771		858		188	
Log-likelihood	-2378.7		-543.3		-104.5	

Notes:

(a) Data are weighted to the population of employees at non-farm workplaces with 20 or more employees.

(b) Standard Errors are adjusted for clusters in workplace identifier.

(c) All specifications include a set of *individual specific variables* (a quadratic polynomial in tenure, five dummy variables for educational attainment, a dummy variable for fixed contract employment, a dummy variable for full time job, a dummy variable for non-production job); a set of *workplace-specific attributes* (private sector, workplace size, whether this workplace has engaged with training in the last two years); a set of *product market attributes* (private sector, whether competing with foreign firms, a set of dummy variables for domestic competition); a set of variables capturing the nature of *workplace organizational change* (Organisational Restructuring=0,1), (Task Restructuring=0,1), (Casual workers up=0,1).

(d) In the full sample estimation, the age range 25-29 is the omitted age dummy variable.

Table 4a: Bivariate Probit Weighted[(a)] estimation results for Prob(*training*) and Prob(*contr_up*). Workers aged 15+. Robust[(b)] standard errors in parentheses. See notes for Table 2.

			All Workers: training			
	All Workplaces		***Workplaces with Technology Benchmarking =1***		***Workplaces with Technology Benchmarking =0***	
Age 45-49	0.157*	(0.082)	0.176	(0.128)	0.147	(0.110)
Age 50-54	0.033	(0.092)	-0.023	(0.140)	0.099	(0.126)
Age 55+	-0.159	(0.105)	-0.178	(0.155)	-0.132	(0.150)
New off. Tec	0.307***	(0.072)	0.147	(0.126)	0.406***	(0.091)
New mach.	-0.017	(0.072)	-0.147	(0.119)	0.045	(0.095)
Tec. Bench	0.102**	(0.041)	____	____	____	____
Tec. Innovation	-0.037	(0.027)	-0.018	(0.045)	-0.067*	(0.036)
Tec. Diffusion	0.029	(0.032)	-0.090*	(0.053)	0.102**	(0.041)
Contractors up	0.530***	(0.178)	0.565**	(0.276)	0.041	(0.237)
Observations	6448		2678		3770	
			Contractors up[(c)]			
Downsizing	0.560***	(0.097)	0.958***	(0.127)	-0.751***	(0.156)
Seasonal Prod Demand	-0.345***	(0.041)	-0.298***	(0.058)	-0.456***	(0.055)
Unpredictable Demand	-0.303***	(0.050)	-0.380***	(0.068)	-0.120***	(0.069)
Sales Growth	0.199***	(0.068)	0.510***	(0.088)	-0.018	(0.089)
Compete on Price	-0.118***	(0.042)	0.088	(0.068)	-0.309***	(0.056)
Contractors for Increasing Demand	0.311***	(0.086)	0.265***	(0.100)	0.416***	(0.128)
Contractors for Decreasing Demand	0.869***	(0.073)	0.895***	(0.092)	0.842***	(0.113)
Tec. Innovation	0.074**	(0.029)	0.018	(0.046)	0.117***	(0.035)
Tec. Diffusion	-0.147***	(0.032)	-0.073	(0.050)	-0.210***	(0.037)
F(.)*,**,***	20.12***		13.09***		13.23***	
Observations	6448		2678		3770	
ρ *,**, ***	-0.306**	(0.120)	-0.289	(0.184)	-0.034	(0.146)

Notes: *(c)*: The full list of right hand side variables for Pr(Contr_up) includes: workplace size, dummy variables for profit/non profit and government/non-government organizations, dummy variables for broad industrial sectors, dummy variables for workplace technology and organizational change, dummy variables for the intensity of domestic competition, dummy variable for unionization.

Table 4b: Bivariate Probit Weighted[(a)] estimation results for Prob(*training*) and Prob(*contr_up*). Workers aged 45+. Robust[(b)] standard errors in parentheses. See notes for Table 2.

	All Workers aged 45+: training					
	All Workplaces		***Workplaces with Technology Benchmarking =1***		***Workplaces with Technology Benchmarking =0***	
Age 45-49	-	-	-	-	-	
Age 50-54	-0.032	(0.085)	-0.179	(0.140)	0.105	(0.120)
Age 55+	-0.283***	(0.099)	-0.537***	(0.150)	-0.105	(0.137)
New off. Tec	0.172	(0.150)	0.180	(0.259)	0.198	(0.199)
New mach.	-0.129	(0.139)	-0.140	(0.239)	-0.236	(0.192)
Tec. Bench	-0.0008	(0.076)	-	-	-	-
Tec. Innovation	-0.121**	(0.055)	-0.146	(0.111)	-0.135**	(0.068)
Tec. Diffusion	0.089	(0.058)	0.012	(0.117)	0.092	(0.074)
Contractors up	1.005***	(0.365)	0.234	(0.976)	0.663*	(0.384)
Observations	1499		642		857	
			Contractors up[(c)]			
Downsizing	0.328*	(0.187)	0.625**	(0.298)	-0.279	(0.243)
Seasonal Prod Demand	-0.301***	(0.087)	-0.129	(0.150)	-0.378***	(0.118)
Unpredictable Demand	-0.011	(0.108)	0.257	(0.163)	-0.096	(0.142)
Sales Growth	0.356**	(0.140)	0.468**	(0.208)	0.326*	(0.196)
Compete on Price	-0.061	(0.086)	0.270*	(0.151)	-0.270**	(0.116)
Contractors for Increasing Demand	0.413**	(0.172)	-0.055	(0.120)	1.010***	(0.286)
Contractors for Decreasing Demand	0.283*	(0.158)	-0.010	(0.225)	0.320	(0.269)
Tec. Innovation	-0.005	(0.060)	-0.209**	(0.103)	0.096	(0.082)
Tec. Diffusion	-0.111*	(0.062)	0.119	(0.101)	-0.250***	(0.085)
F(.)*,**,***	225.25***		90.32***		179.75***	
Observations	1499		642		857	
ρ *,**, ***	-0.520*	(0.311)	0.037	(0.582)	-0.306	(0.265)

Notes: *(c)*: The full list of right hand side variables for Pr(Contr_up) includes: workplace size, dummy variables for profit/non profit and government/non-government organizations, dummy variables for broad industrial sectors, dummy variables for workplace technology and organizational change, dummy variables for the intensity of domestic competition, dummy variable for unionization.

Table 4c . Marginal effect of an increase in outsourcing on workers' training, various samples, AWIRS 1995. Marginal effects are computed as [Pr(*training*|*Contr_up*=1)- Pr(*training*|*Contr_up*=0)].

	Workers aged 15+			**Workers aged 45+**		
	Full sample	Production	Non-Production	Full sample	Production	Non-Production
Pr(*training*|*Contr_up*=1)	0.354	0.075	0.260	0.265	___	0.235
Pr(*training*|*Contr_up*=0)	0.018	0.003	0.014	0.014	___	0.013
Marginal Effect of *Contr_up*	0.336	0.072	0.246	0.252	___	0.223

Table 5a: Kernel densities of estimated propensity scores: All workers aged 45 and +

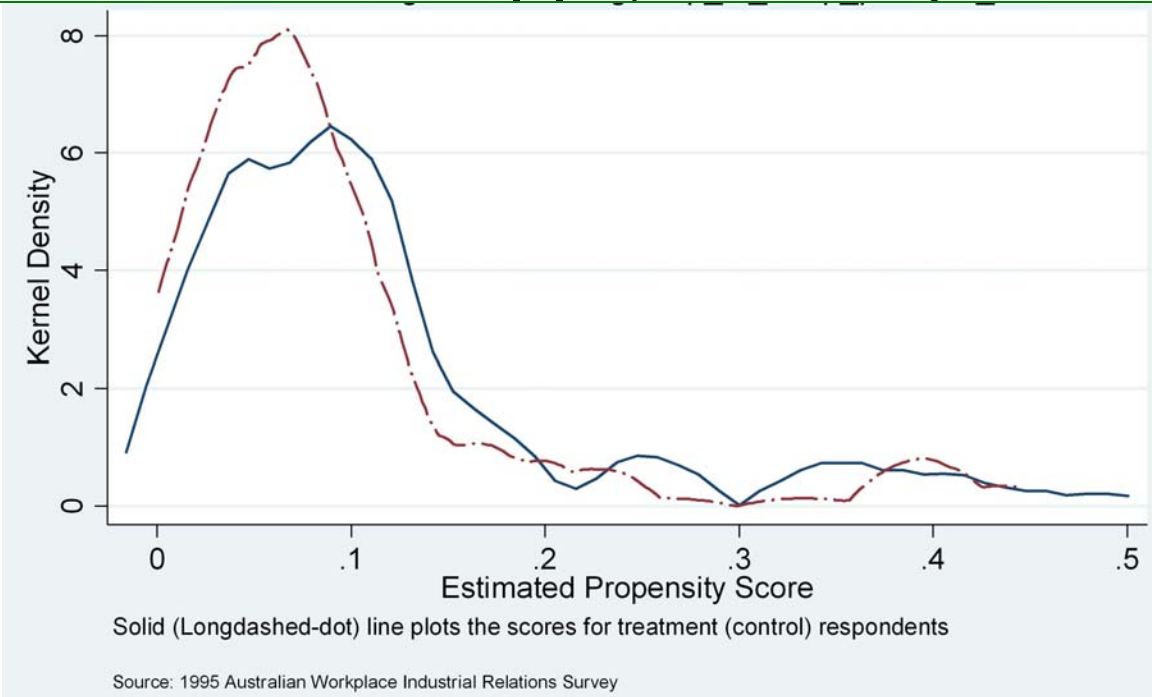


Table 5b: Kernel densities of estimated propensity scores: All workers aged 15 and +

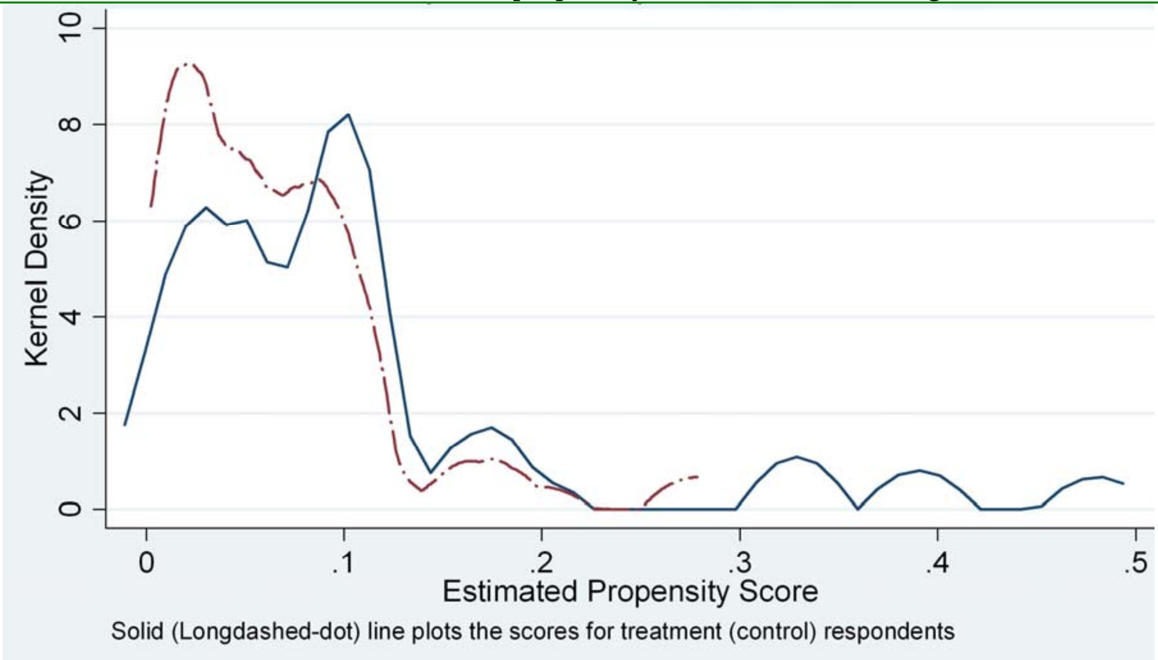


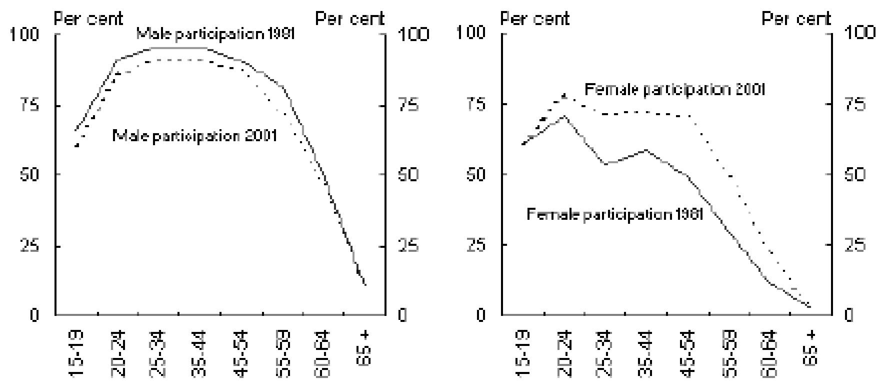
Table 5c: Average Treatment effect of an increase in outsourcing on the probability of training

	Size of treated sample	Size of control sample	ATT	S.E.	t-statistics
Workers aged 45+	192	3917	0.083	0.039	2.12
Workers aged 15+	741	15050	0.032	0.019	1.69

Note: Standard errors are computed by means of the bootstrapping option.

Figure 1: Labour Force Participation Rates by age and gender, Australia, 2003

Chart 2: Labour force participation rates, males and females by age



Source: Australian Bureau of Statistics, *Labour Force, Australia, Detailed - Electronic Delivery*, cat. no. 6291.0.55.001, Canberra, 2003.