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ABSTRACT

Using longitudinal data for Canada, the probability of participating in employer supported course enrollment for mid career workers and the wage impacts of those adult educational investments are analyzed. Probability of participation in employer supported course enrolment is increasing with age, job tenure and education, and is lower for visible minority workers. Using a parametric difference-in-differences model to minimize the effects of selection into training, we find strong positive effects of employer supported course enrollment on wage changes over time. The estimated effect ranges from 6.8 to 7.7 percent wage growth for men and 7.5 to 9.3 percent wage growth for women. When the linear specification of the outcome equation is relaxed and an empirical common support is implemented through semiparametric difference-in-differences matching methods, the average treatment effect on the treated estimates from the log wage change models were smaller in magnitude than the corresponding parametric estimates but were typically still statistically significant and in the range of 4.2 to 7.6 percent for men and 7.6 to 7.1 percent for women. An analysis of respondents' health outcomes shows no clear relationship with participation in employer supported course enrollment.

JEL: C14, J24, J31, M53

Key Words: return to adult training, employer sponsored training, difference-in differences models, propensity score matching.

Executive Summary

We analyze the incidence and returns to adult (age 25 and older) training and education for women and men in Canada using the confidential files of the two most recent Survey of Labour and Income Dynamics (SLID) panels of Statistics Canada – panel 4 (2002-2007) and panel 5 (2005-2009). The probability of participation in employers supported course enrolment is lower for visible minorities relative to non-visible minority workers, and increasing with education.

We employed a parametric difference-in-differences methodology to estimate the causal impacts of employer supported course enrollment and mid career investments in formal education on wages. Results show statistically significant positive effects of employer supported course enrollment on wage growth. The estimated effect ranges from 6.8 to 7.7 percent for men and 7.5 to 9.3 percent for women. The same results emerge when restricting the sample to workers with less formal education. When we control for hours spent in education over the panel window for those enrolled in employer supported courses, on the other hand, we find a small but positive effect on wage growth for men but not for women.

The same exercise was carried out over sub-samples of less educated workers to see whether these course enrollment investments are especially beneficial for workers with less formal education. Using the: 1) high school diploma or lower education, and 2) the below university degree criteria to define sets of less skilled workers, we re-estimated our wage growth model. In each case, the estimated effects on wage growth of enrollment in employer supported course enrollment were similar to what was found in the estimation carried out over the sample of all workers.

Because parametric difference-in-differences estimates may suffer from additional sources of bias i.e., false linearity assumptions and lack of common support, propensity score matching methods were implemented. The average treatment effect on the treated estimates from the wage models were smaller in magnitude than the corresponding parametric estimates but were statistically significant and in the range of 4.2 to 7.6 percent for men and 7.1 to 7.6 percent for women. This finding suggests the importance of imposing an empirical support region in this data.

Furthermore, this study analyzes differential returns to employer supported course enrollment by immigration status. Results from matching methods show large point estimates for recent immigrant men (28.3 percent in panel 5 and 40.2 percent in panel 4). For women, on the other hand, the point estimates are not significant. This is an important area for future research, possibly involving new sources of data where a larger sample of recent immigrants is present.

The final part of our analysis involved a preliminary investigation into possible effects of employer supported course enrollment on non-labour outcomes. Due to data limitations, we focused on adult health outcomes. By using propensity score matching methods, we found some evidence of a positive relationship between employer supported course enrollment and self-reported health outcomes. However, this finding is not robust to the choice of panel. Clearly, this is an area warranting further research.

1. Introduction

Our focus is on the incidence and returns to adult (age 25 and older) training and education for women and men in Canada. Using longitudinal data from the confidential versions of the Survey of Labour and Income Dynamics (SLID) of Statistics Canada, we analyze the impact on wage outcomes after re-entry into the labour market, of mid-career investments in education and job training. A key question of interest relates to whether these types of adult educational investments yield a higher (or lower) return for relatively less educated individuals relative to their more educated counterparts. Individuals who enter the labour market with relatively low levels of education often find that they lack the necessary human capital and credentials needed to adapt to the rapidly changing labour market in Canada that has existed over the past 35 years. The severe recession of the early 1980s and early 1990s coupled with the restructuring in the labour market caused by the introduction of the US-Canada Free trade Agreement, the North American Free Trade Agreement, the High Tech Meltdown in the early 2000s and the recent Financial Crisis have had major implications for the stability and expected duration of jobs. Within this context, it is more and more likely that mid-career investments in both human capital and credential acquisition will be needed in order for workers to both retain stable employment and receive a suitable return on their past investments in human capital.

This study exploits the longitudinal structure of the SLID data and implements standard parametric difference-in-differences models to shed light on the effectiveness of mid-career investments in the Canadian labour market. The type of learning analyzed in this study pertains to higher education, primarily employer sponsored course enrollment, as well as ‘other-labour market’ forms of human capital investments. The outcomes of interest are measured at the individual level (for example, higher hourly wage rates after the human capital investment). The main finding shows positive and statistically significant wage returns of 7 to 9 percent for both men and women participants in employer supported training courses. The estimated wage premiums drop by up to 38 percent when the linear specification of the outcome equation is relaxed and an empirical common support is implemented through semiparametric difference-in-differences matching methods. This may suggest that the parametric specification estimates suffer from self-selection bias.

This project is one part of a larger research program, the *Adult Learning and Returns to Training Project,* a multi-disciplinary research program. The remainder of the paper is organized as follows. Section 2 provides a literature review. Section 3 develops the empirical methodology, while section 4 describes the data. Sections 5 and 6 present the parametric results, while section 7 shows the semiparametric matching approach along with its results. Finally, section 8 analyses additional social outcomes. Section 9 places our analysis within the broader typology and analytical framework of the *Adult Learning and Returns to Training Project,* and section 10 concludes.

2. Literature Review

In the last two decades, the availability of micro household data along with the theoretical development of new econometric estimators has fueled research on the causal effects of education and training on labor-market outcomes (Heckman 2003). As a result, research on the economic returns to investments in human capital is extensive and well documented across countries and demographic groups (see Card 1999 for a survey). Whether it is formal education, or employer-sponsored training, the empirical evidence supports the connection between investments in human capital and success in the labor market. Results for developed western economies suggest, for instance, that the economic return for an extra year of formal schooling ranges between 5 to 15 percent (Blundell et al. 1999, Card 1999). This is in line with the theoretical literature that predicts that in competitive markets where wages reflect marginal productivity, more educated workers have higher earnings than their less educated counterparts.

Canada has not been the exception and particular research emphasis has been given to the study of returns to formal education. The consistent picture that emerges from several studies that use Canadian data is the statistically significant returns to formal education in the marketplace. The estimates range between 3 and 15 percent depending on specific demographic groups. Women, for instance, are found to have consistently higher returns to formal education than are men (e.g., Bar-Or et al 1995, Beaudry and Green 1998, Card and Lemieux 2001).

Yet, there is no consensus in the literature regarding the evolution of the economic returns to education in Canada. While some studies report a stable (or declining) returns to formal education (e.g., Dooley 1986, Burbidge, Magee and Robb 2002, Freeman and Needles 1993), other studies report an increasing trend (e.g., Bar-Or et al 1995, Beaudry and Green 1998, Card and Lemieux 2001, Boudarbat, Lemieux, and Riddell 2006). The latest evidence suggests that the failure to control for age/experience along with the use of small sample sizes accounts for these differences (Boudarbat, Lemieux, and Riddell 2010). This result accord with previous research in Canada that suggested increasing returns to experience in the last twenty or so years (Picot 1998, Morissette et al. 1999).

As human capital investments involve the accumulation of knowledge, skills, and competences acquired through formal education and life-long training, the interaction between returns to formal education and returns to adult training is itself a topic of interest. Two particular features of the Canadian educational system are worth mentioning in this regard. First, there is a high degree of heterogeneity in the provincial school systems in Canada. Thus, a high school diploma may require between 11 and 13 years of education depending on geographic location and age cohort, while a bachelor degree may require three to five years of study depending on the type of university and program attended. Second, it is common to observe individuals in the marketplace who combine university bachelor degrees with community college or trade school certificates. Indeed, about a quarter of university graduates report having a community college or trade school certificate (Ferrer and Riddell 2002). Likewise, 36 percent of the workforce reports having a non-university post-secondary certification, in the form of either a college diploma or a trade certificate, or university certificate below a bachelor degree (Ferrer and Riddell 2002).

These salient characteristics suggest a relatively broad range of combinations of credentials in the Canadian labor markets. This has implications for the measurement of the returns to education as each year of schooling does not contribute equally and independently to productivity. In this regard, Ferrer and Riddell (2002) showed the existence of strong non-linearities in the returns to education when simultaneously considering both the receipt of a degree and years of schooling. The authors show that 30 percent of the returns to completing 16 years of schooling is explained by 'sheepskin' effects, which confirms previous suggestions made in Vaillancourt (1995), Cote and Sweetman (1997), and Parent (1999).

Given that credentials matter in the labor market, an important topic relates to the interplay between educational attainment and life-long learning certification, since it is well documented that complementarities exist between formal education and further acquisition of skills and competences, due to the cumulative nature of human capital formation (Murnane et al. 1995, Blundell et al 1999, Heckman and Vytlacil 2001). As ‘learning begets learning’ (Heckman 2003), the set of incentives and barriers to undertake further post-schooling training depends on the current stock of human capital. Available evidence for developed countries shows that individuals with relatively low educational attainment, no previous training experiences, and from low social and economic status, are less likely to participate in adult education and training (Carneiro and Heckman 2003, Cawley et al. 2000); while, at the same time, the economic returns for them are higher relative to the returns for more educated workers (Blundell et al. 1999, Ashenfelter and Rouse 1998, Heckman et al. 1999).

Unlike the broad literature on returns to formal schooling, few studies have addressed the returns to education and training programs among adult learners in Canada. It is well documented that the overall participation of adults in training programs has consistently increased in the last decades (Haggar-Guenette 1991, Gower 1997). Official statistics show that around one third of the workforce participated in formal adult programs or courses in recent years (Statistics Canada 2004), although the level of participation in employer-sponsored training was stagnant during the same period[1]. The majority of this adult learning participation is job-related and does not lead to certification. Consistent with the “learning begets learning’ hypothesis, Myers and Myles (2005)

[1] The proportion of workers who receive support from their employers has declined since 1997, from 79 percent to 72 percent. As a result, the incidence of employer-sponsored training is much lower in Canada than in some European countries, (OECD 2003)

find that more educated workers are more likely to participate in adult learning training relative to their less educated counterparts in Canada.

This literature has made an important distinction between participation in publicly sponsored training programs and lifelong learning education and training. The former targets particular groups of disadvantaged individuals and provides them a particular 'treatment' once eligibility conditions are satisfied. The latter is mostly job-related and the result of individuals' choices to update labor-market skills and competences. It can take the form of employer-sponsored training programs. In this regard, a consistent pattern that emerges from the literature is the striking differences in the effectiveness of government- and employer-sponsored training programs. While participants in government-sponsored training program show modest or no wage premiums in western developed economies (see Heckman et al. 1999 and Card, Kluve and Weber 2009 surveys), participants in employer-sponsored training programs show high and statistically significant wage returns (see Lillard and Tan 1986, Barron, Berger and Black 1997, and Almeida and Carneiro 2009).

This divergence in the effectiveness of employer- and government-sponsored training programs has not been fully explained in the literature yet. Heckman et al. (1997) and Carneiro et al. (2002) suggest this result as a failure of the available employer-sponsored training datasets to completely control for key unobserved covariates of interest. A more recent study by Kamnourov, Manovskii and Plesca (2010) shows an overlooked selection mechanism that might explain this pattern. The occupational mobility for individuals who self-select into government-sponsored training programs is different than that for individuals participating in employer-sponsored training programs. The likelihood of switching jobs after training is higher for the former than that for the latter, which causes a substantial destruction of human capital in the short-run with the corresponding reduction in labor-market earnings. Once, occupational mobility is accounted for, wage premiums for both types of training are similar and statistically significant different from zero.

Nonetheless, evidence on the effectiveness of government employment and training programs in Canada is limited. An exception is the evidence on job search assistance programs based on the widely known Self-Sufficiency Project, summarized in Michalopoulos et al. (2002) and analyzed in a large number of research studies (e.g., Foley and Schwartz 2002, Card and Hyslop 2004, Michalopoulos et al. 2005, Zabel et al. 2004). Few studies, on the other hand, have addressed adult education and training returns (and only in recent years) and with mixed results. Smith and Hui (2003) estimate the labor-market impacts of participation in adult education and training using the 1998 Adult Education and Training Survey (AETS), a cross-sectionally representative survey of the Canadian workforce. These authors find quite unreliable estimates for several widely used econometric estimators, which lead them to believe that the primary problem with the estimates lies in the data rather than in the estimates. Myers and Myles (2005) analyzed whether formal adult learning increases the likelihood of receiving higher income and promotion using data from the 2004 Changing Nature of Work and Life-Long learning (WALL), a nationally representative sample of the adult population in Canada[2]. The authors reports positive and significant impacts of training in the outcomes of interest after implementing a standard multivariate linear regression. Most important, this study reports that less educated workers were more likely to report a positive labor-market benefit from training relative to their more educated

[2] Myers and Myles (2005) also use data from the Adult Education and Training Survey (AETS).

counterparts. This research is in line with the overall pattern emerging from studies abroad that suggests that the least educated are less likely to participate in life-long formal learning, but when they do participate, they receive higher economic returns than do more educated workers (e.g., Blundell et al. 1999).

Evidence on the effectiveness of employer-sponsored training programs in Canada was even thinner up until recently. The availability of new datasets such as the Statistics Canada's nationally representative Workplace and Employee Survey (WES), which targets employer-sponsored training programs has spurred the generation of several labor-market studies in recent years. We have preliminary evidence on the determinants of worker participation (Belzil and Hansen 2006, and Gagnon and Doray 2005), training intensity at the establishment level (Chaykowski and Slotsve 2006, and Turcotte *et al* 2003), and impacts of training on firm-level performance measures (Morissette and Rosa 2003), firm-level productivity (Turcotte and Rennison 2004, Dostie and Pelletier 2007), and wage premiums (Drolet 2002, Yoshida and Smith 2005, Havet 2006, Dostie and Leger 2011).[3] In particular, all studies that measured wage premiums for employer-sponsored training programs fund positive and statistically significant impacts, albeit smaller impacts relative to the broader international literature.

More closely related to our research design are the studies by Zhan and Palameta (2006) and Drewes (2008) who addressed the economic returns to adult education and training in Canada using longitudinal data from the Survey of Labour and Income Dynamics (SLID), a panel containing representative household data. The former used two complete panels, the 1993-1998 and 1996-2001, while the latter used a richer set of information on formal education and training

[3] With the exception of two studies, this research work is still unpublished.

activities undertaken by adult workers and sponsored by firms. The picture that emerges from these studies suggests that formal adult education and training in Canada have positive and statistically significant returns, ranging between 3 and 10 percent, while training programs that lead to certification have higher returns than that for non-credit training courses. Moreover, the initial schooling level is strongly correlated with participation in further adult education and training programs. These results accord with the findings reported in Frenette (2010) that uses data from the Longitudinal Worker File (LWF), an administrative data survey that follows displaced workers five and nine years before and after displacement.

Overall the patterns on participation in and returns to adult education and training programs is externally validated by studies that used data from the U.S., although to lesser extent with research for some European countries. For instance, Leigh and Gill (1997) and Jacobson et al. (2003) report positive and significant returns to one year of community college in the U.S. for adult workers, while Jenkins et al. (2002), Ekstrom (2003), and Albrecht (2004) report no impacts on earnings for adult education and training programs in the United Kingdom and Sweden.

3. Methodology

There are two main parts to our empirical analysis. First, using SLID data, we analyze the incidence of participating in employer supported training programs. The index of the binary choice model has the following general form:

$$I_{it} = Z_{it}\alpha + \varepsilon_{it} \tag{1}$$

where I_{it} is a latent index which is greater than or equal to zero if the respondent participates in employer financed training and is negative otherwise; Z_{it} is a vector of personal and job characteristics such as age, gender, marital status, visible minority status, immigrant status, job tenure, highest level of education, industry, province of residence, firm size and occupation; α is a parameter vector; and ε_{it} is a mean zero error term.

Next, using the longitudinal nature of the SLID data, we analyze the change in the log wage of individuals according to two dimensions: i) cases where the person has participated in workplace training and ii) cases where the person's highest level of education has increased during the period covered by the relevant SLID panel. The general form for these log wage change models is:

$$lnY_{it+j} - lnY_{it} = \alpha + \delta lnW_{it} + X_{it}\beta + Inv_i\gamma + u_i \qquad (2)$$

Where Y_{it+j} is respondent *i*'s hourly wage rate in the final year of the panel and Y_{it} is his/her hourly wage in the first year of the panel. X_{it} is a vector of personal characteristics; Inv_i is a measure of human capital investment activity over the panel period; γ is a parameter vector and u_i is a mean zero error term. This approach is very similar to the model employed by Zhang and Palameta (2006) which they motivate using the earnings growth literature studies (such as Podgursky and Swaim, 1987). In this case, γ, can be interpreted as roughly equal to the percentage growth in the log hourly wage rate from the educational investment.

We employ several approaches to measuring the human capital investment variable, Inv_i. First, we define an indicator variable that equals one if the respondent reported taking an employer supported course in any of the panel years. This variable is used as the main measure of adult education participation in our analysis. In addition, we also develop a measure of intensity of investment in which we add up the total number of hours spent in course enrollment in each of the panel years and use this as the measure of Inv_i. Finally, we also create indicator variables for cases where the respondent's level of formal education shifts from one category to a higher category between the first and final year of the panel. For example, for individuals with less than a high school diploma in the first year, if they report in the final year having either completed high school, or having some level of post-secondary education, then the variable equals one, otherwise, it equals zero.

In addition to our analysis of log wage changes across the years of the panel, we also investigate the possible impact of adult education investments on non-wage outcomes. In particular, we use the self-reported health information in the SLID to see whether adult education leads to a change in health outcomes.

The methodology used in the estimation of the wage return model, (2), corresponds to a difference-in-differences model in the following sense. The inter-temporal difference in the log wage for the treated group is measured as a difference from the inter-temporal difference in the log wage for the comparison group (those who did not have the human capital investment). This approach can remove any potential bias coming from time-invariant unobserved factors such as motivation and ability. The fundamental assumption behind this model is that, in the absence of training, the change in log wages for trainees and non-trainees follow parallel paths. This example could be violated by period effects being different for the two groups. For example, if macroeconomic effects impact the treatment and the comparison group in different ways then this would tend to bias our estimates of the returns to the new education.

It should be noted that our approach to measuring the return from these mid-career investments in human capital focuses on the wage benefits (and to a limited extent any other social benefits) from the investments and not the costs of these investments. Due to a lack of information, we do not incorporate the costs of the human capital investments (e.g. tuition costs) so we are not measuring a net return to the human capital investments.

4. Data

We use the confidential files of the two most recent Survey of Labour and Income Dynamics (SLID) panels – panel 4 (2002-2007) and panel 5 (2005-2010)[4]. However, the indicator of whether or not the person is enrolled in the employer-supported course is only available from 2002 to 2008, which makes the longitudinal tracking in Panel 5 to last for five years compared to six years in Panel 4. This will restrict our possibilities to have a balanced analysis of the two full panels when the employer-supported course participation variable is used. Unlike the earlier panels, these contain the most detailed information related to employer support of training and education. The sample is restricted to individuals age 25 to 55. The lower bound for age is chosen in order to restrict attention to individuals who likely have completed their initially 'planned' schooling and entered the labour market for the first time. The upper age restriction is chosen to abstract from retirement ages. This is especially important given our interest in understanding the impact of educational investments on post-training wage outcomes.

[4] Individuals in panel 4 are tracked for six years from 2002 to 2007, while our sample in panel 5 only has five years of tracking from 2005 to 2009 due to the absence of the variable of the employer-supported course enrolment in 2009 and 2010 of panel 5.

In Table 1, weighted means of a number of the key variables used in our analysis are presented separately for males and females and separately by SLID panel.[5] The employer-supported course enrollment variable equals one if the respondent reported being enrolled in a course with the support of his/her employer in any of the years of the panel[6]. The proportion of men reporting this is 29.9 percent in panel 4 and 27.6 percent in panel 5. For women, the proportion is 26.9 percent in panel 4 and 24.4 percent in panel 5. In the second row, we provide the mean hours spent in employer supported course enrollment over the panel time period. Each survey year of each of the two SLID panels includes a question on hours spent in course enrollment that year. Unfortunately, the question does not distinguish between time spent in course enrollment with and without employer support. Our approach to approximating the total time spent in employer supported course enrollment is to identify the years in which the respondent identified employer supported course enrollment and then aggregate the total hours spent in course enrollment over those years. This will be an upwardly biased estimate of the total hours spent in employer supported course enrollment since some respondents may do both: 1) course enrolment without employer support, and 2) course enrollment with employer support, in the same year. For men, mean hours in employer supported course enrollment is 88.0 in panel 4 and 59.8 in panel 5. For women, the equivalent figures are 69.4 and 46.7. Therefore, while the incidence of employer supported course enrollment is only three percentage points higher for men, the average number

[5] In each part of the analysis, we employed the SLID longitudinal weights.

[6] The person will be identified to be in employer-supported courses if he/she reports to participate in the employer-supported course in at least one of the years from 2003 to 2006 in panel 4, while the person in panel 5 needs to take the course in at least one of the years from 2006 to 2008. Therefore, panel 5 is the panel with shorter survey years when compared to panel 4.

of hours spent in this form of adult education is 13-19 hours higher for men across the two panels.

In Table 1, we also report the breakdown by level of education in the first year of each panel. The distributions for men and women follow the patterns that one would expect and are very similar across the two panels also as expected. In the bottom panel of the table, we present other key characteristics of our respondents based on how they are reported in the first year of each panel. As expected, hourly wage rates are higher for men than for women in each panel as is the case for months of job tenure. The immigrant proportion of the sample is 20 to 22 percent while the proportion of recent immigrants is 6 to 7 percent for those arriving the past 10 years and 3 to 4 percent for those arriving in the previous five years.

5. Participation in Course Enrollment

Next, we employ multivariate analysis to explore the decision to participate in employer supported training using logit estimation of a binary choice model. This will help us to understand the possible selection into employer supported training and identify observable characteristics that may be associated with this selection.

Table 2 reports logit estimated coefficients of covariates that potentially have significant impacts on employer-supported course enrollment.[7] Data employed in the estimation of Table 2 are drawn from Panel 4 (2002-2007) and Panel 5 (2005-2009) of SLID and are analyzed separately. Each panel was balanced by requiring that observations on all variables were available for each

[7] Fixed effect Logit estimation was also employed and resulted in insignificant estimates on most covariates due to relatively little variation in the explanatory variables over time.

year of the panel. Longitudinal weights were used in the estimation. In this part of our analysis, the unit of observation is the person-year.

Probability of employer supported course enrollment is not found to vary with age with the exception of the case of women in Panel 4 where a positive and concave relationship is found. The coefficients on the job tenure controls are typically significant but the magnitudes of the effects are quite small. Participation in employer supported course enrollment is lower for visible minority workers (relative to the Canadian born, non-visible minority reference group) and for immigrants; however, the result for immigrants is not robust in the sense that the estimates are positive but very close to zero in the panel 5 estimation. Finally, the probability of participating in employer supported course enrollment is increasing in the respondent's level of education with especially large effects at the university level.

6. Determinants of Hourly Wage Growth over each Panel

Next, we exploit the longitudinal nature of the SLID data to measure actual log wage changes between the first and final year of each panel. Using the respondent's log wage change as the dependent variable, we carry out a multivariate regression estimation to see whether the change in the log wage varies according to the investment activities of particular interest: 1) employer supported course enrollment, 2) total number of hours of training, and 3) increases in formal education.

6.1 Effect of Employer Supported Training on Wage Growth

In Table 3, results are presented from the log wage change model estimated separately across the two panels and separately for women and men[8]. A rich set of controls are included in the econometric model: age, marital status, visible minority status, immigrant status, job tenure, education level, industry, occupation, firm size and province of residence. We focus our discussion on the indicator variable for having participated in employer supported training. This variable takes a value of one if at any time over the panel period, the person reported having undergone employer supported training, and a value of zero otherwise. The change in the log hourly wages rates of workers who take employer supported courses is higher than that of employees who do not take employer-supported courses. The estimated effect is approximately 6.8 percent and 7.7 percent for men in Panel 4 and Panel 5, respectively, and 9.3 percent and 7.5 percent for women in Panel 4 and Panel 5, respectively. These estimates are each individually statistically significant at the one percent level which indicates robust support for the idea that employer supported courses lead to higher wage growth for both men and women in Canada. Despite differences in the definition of adult training, samples, econometric specification and timing of activities, these estimates are consistent with both international and domestic evidence about the positive and statistically significant wage impacts of employer sponsored adult education and training (e.g., Yoshida and Smith 2005, Zhang and Palameta 2006)

In Table 4, regression results are presented from an equivalent change in log wage rate model but where the indicator variable for enrollment in an employer supported course is instead replaced

[8] Note that in order to compare the results across panels; we only use the data from the first five survey years of panel 4. However, the estimation results obtained using the complete six survey years for panel 4 is presented in Table A1 in the appendix. We use the term ‘short waves’ to denote tables in which we only use the first five survey years of panel 4, and we use the term ‘long waves’ to denote tables in which we use all six survey years of panel 4.

by a measure (defined above) of the total time spent in employer supported courses over the panel period. The effect of the number of hours in employer-supported course enrollment is positive and significant at 0.000205 to 0.000242 for men. For women, the coefficients are of similar size and magnitude but not individually statistically significant. Focusing on the significant results for men, this indicates that a 100 hour long course can lead to approximately a 1.7 percent increase in wage growth over the panel period. Given that the sample mean for total hours in course enrollment (for those who take courses) is smaller than 100, this indicates an average effect of course enrolment that is smaller than what was found in Table 2 where the indicator of course enrollment was employed. One possible explanation is that respondents do not recall accurately the number of hours spent in these courses. This measurement error would lead to attenuation bias of the coefficient on the hours variable, biasing it towards zero. Given this concern, we focus on models that employ the course enrollment indicator as the measure of human capital investment in the remaining analyses related to employer supported course enrollment in this paper.

6.2 Wage Growth Impacts of Employer Supported Training for Immigrants

Immigrants to Canada face a number of challenges related to having their foreign educational credentials and work experience recognized by employers in Canada. Given the well-documented difficulties faced by cohorts of immigrants arriving in Canada since the 1980s (see, for examples, Aydemir and Skuterud, 2005, and Green and Worswick, 2012), a natural question to ask is whether employer supported training allows immigrants to gain the necessary credentials or missing human capital so as to begin to have high returns to their pre-migration human capital. This could lead to much higher returns to employer supported course enrollment for immigrants than for the Canadian born since the small investment in training post migration may allow for the under-valued pre-migration human capital to become valued at or near the level that equivalent training in Canada would be valued in the Canadian labour market.

In Table 5, we present estimates of the log wage change model from Table 3 but with an interaction of the course enrollment variable with an immigrant indicator. We estimate three versions of the model and each panel of Table 5 relates to the key variables in each case. First, we interact the course enrollment variable with an indicator for all immigrants. Next, we re-estimate the model with the immigrant interaction variable being for the case of immigrants who have been in Canada for 10 years or less as of the first year of the panel. Finally we re-estimate the model and interact the enrollment variable with an indicator for immigrants who had been in Canada for five years or less as of the first year of the panel. The coefficients on the interaction variables are in general positive but in most cases they are not statistically significant. However, there are a few exceptions. The interaction coefficient for the case of women in panel 4 implies a 10.2 percent increase in the wage for these immigrant women in addition to the 8.2 percent increase experienced by non-immigrant women. However, the same relationship is not found for immigrant women in panel 5. Once the focus is placed on more recent immigrants who are likely to need to make post-migration investment in human capital, we see a pattern of positive coefficients, but they are only statistically significant in the case of panel 5 where the extra return to course enrollment is 10.4 percent when recent immigrants are defined as having been in the country not more than 10 years, and is 17.3 percent when recent is defined as 5 years or less. While the findings are not robust to choice of panel, there is enough evidence of higher return to employer supported course enrollment for recent immigrants to suggest further research, possibly involving new sources of data where a larger sample of recent immigrants is present.

6.3 Wage Growth Effects of Employer Supported Course Enrollment for Less Skilled Workers

Next, we focus on workers with relatively less formal education and consider whether the impact of employer supported course enrollment differs for less educated workers relative to all other workers. In doing this, we consider two definitions of less skilled workers: 1) those with a high school diploma or less education and 2) those who do not have a university degree. In the first row of Table 6, we present the coefficient on the course enrollment variable based on a model equivalent to that used in Table 3 but estimated over the sub-sample of workers with a high school diploma or less education.[9] In the case of panel 5, the estimate is strongly statistically significant indicating higher wage growth for workers who participated in employer supported course enrollment (relative to those who did not) at 9.2 percent for men and 12.2 percent for women. However, the equivalent estimates from panel 4 are closer to zero and not statistically significant.

The same exercise was carried out over a somewhat larger sub-sample, individuals with education below the university degree level, and the coefficients on the course enrollment indicator are reported in the second row of Table 6. Scanning across the row, we see quite stable estimates with almost identical impacts of employer supported course enrollment for female at 8.5 to 8.6 percent and a small increase for male at 6.7 to 8.6 percent. These estimates are very similar to what was found in Table 3. Therefore, our analysis of less skilled workers suggests

[9] Each cell of Table 6 is taken from a separate regression estimation of the log wage change model from Table 3. In order to reduce the total number of tables in the paper, we present only the relevant coefficient estimate, its standard error, and the number of observations used in the estimation.

that the impact on wage growth of employer supported course training does not differ substantively from that of the entire workforce.

6.4 Effect of Additional Formal Education on Wage Growth

Next, our wage change model is extended to consider the impact on wage growth of increases in formal education over the panel window. This is determined by comparing the education level of a person in the final year of the panel to the education level of the person in the first year of the panel. We estimate a model that is similar to that of Table 3, but we replace the indicator for course enrollment with an indicator of formal education upgrade then interact it with each of the education indicator variables to allow for differential impacts of educational upgrade one the change in the log wage rate according to the initial education level of the individual.

In the first row of Table 7, we see the coefficient on the upgrade indicator which corresponds to the educational upgrade for the default education level – those with less than a high school diploma. The lower rows of the table pertain to the interaction effects for each of the other education levels[10]. In general, very few of these coefficients are statistically significant.
For example, the coefficient on the upgrade from a high school diploma estimated for women in panel 4 is significant at the 10 percent level and implies a 14.1 percent effect. The coefficients in panel 5 show the positive significant impacts of the educational upgrade from each initial education attainment of all the levels above under high school for males. The magnitudes of the impacts for males in panel 5 range from roughly 18 percent to 25 percent in terms of increasing the log wage rate due to the formal educational upgrade from different education levels.

[10] Due to a lack of observations, it was not possible to estimate the model for the case of individuals with degrees above the bachelor level.

Although the results have shown strong positive effects for males in panel 5, many of the other coefficients are positive, consistent with an increase in the change in the log wage due to the increase in formal education. However, the standard errors are also large which is likely due to the small sample sizes given the infrequency of these investments for mid-career workers. It may be necessary (in future work) to combine SLID panels (perhaps also combining men and women) in order to increase the number of observations in order to generate more precise estimates of these effects. Given this lack of precision, we focus in the remainder of the paper on the effect of employer supported course enrollment on the change in the log wage rate. Further investigation of the wage impacts of formal educational investments mid-career is left for future work.

7. Endogeneity of the Decision to Invest in Employer Supported Course Enrollment

The parametric difference-in-differences estimates presented in the previous section may suffer from two sources of bias. The first bias arises from the linearity assumption that could mask the relationship between wage outcomes and training participation measures. The second bias will arise if different distributions of the vector of observable variables *x* between training participants and non-participants groups occur (Heckman et al. 1997).

To address these concerns, we implement a difference-in-differences matching estimator (Heckman et al. 1998), which is a conditional semiparametric version of the widely used parametric approach. In general, standard matching methods minimize selection issues by pairing training participants (i.e., the treatment group) to comparable non-participants (i.e., comparison group) based on a set of observable covariates. By using observations in the treatment and comparison groups over the region of common support and by reweighting the comparison group observations one eliminates concerns about the "comparability" of the treatment and comparison groups. Let Y_1 and Y_0 be the potential wages for trainees conditional in participation and non-participation. Let $T \in \{0,1\}$ indicate training participation. For any individual, only one component of *T* can be observed in the data. The data we observe for each unit is therefore *(Y,T,X),* with *x* a vector of pre-treatment covariates and *Y* the observed wages. The identification of the counterfactual outcome is possible after invoking the conditional independence assumption (CIA): $T \perp Y_0 \mid x$

This assumption states that assignment to training is unconfounded conditional on a set of pre-treatment covariates, *X*. It rules out any systematic selection into levels of the treatment based on unobserved characteristics correlated with outcomes. The propensity score will produce valid matches for estimating the impact of the employer's intervention on wage growth if all of the relevant information about enrollment in courses is observable. As we have a rich set of observables in our data set, this exercise provides a valid robustness check. Rosenbaum and Rubin (1983) show that if the CIA assumption holds for *x* then it also holds for the conditional probability of participation or propensity score, $P(X) = \Pr(T = 1 \mid x)$. Replacing *x* with *P(x),* the CIA becomes $T \perp Y_0 \mid P(x)$.

Matching methods force us to compare comparable individuals by relying on the common support assumption $\Pr(T = 1 \mid x) < 1$ for all *x*. The support condition ensures that for each *x* satisfying the conditional independence assumption there is a positive probability of finding a match for each treatment individual. Otherwise, if there are *x* for which everyone received treatment, then it is not possible for matching to construct the counterfactual outcomes for these individuals.

Under these identification conditions, we implement the difference-in-differences matching estimator to the available panel data. By using longitudinal data, this estimator identifies the parameter of interest without discarding selection into treatment on the basis of time-invariant unobserved variables. Thus, training impacts are measured as before-after differences to remove the effects of time-invariant unobserved characteristics that potentially affect both training participation and the outcome of interest.

We estimate the average treatment impacts for trainees (ATT) by computing first the counterfactual outcome for each individual in the treatment group (who received support from their employers to enroll in courses) by using a weighted average of the outcomes in the comparison group (who do not enroll in courses with employer support), and then averaging these results over the treatment group sample

$$\Delta^{ATT} = \frac{1}{n_1}\sum_{i \in n_1}\left\{[y_{it+j} - y_{it}] - \left\{\sum_{k \in n_0} w(\rho_i - \rho_k)[y_{kt+j} - y_{kt}]\right\}\right\}. \quad (3)$$

where n_1 and n_0 are the sample of treatment and comparison group individuals $\rho_l = P_l\ (x)$ for l= *{i,k}* is the conditional propensity score, $w(\rho_i - \rho_k)$ is a kernel weighting function that depends on the (Euclidian) distance between the conditional propensity score for each individual *k* in the comparison group and the conditional propensity score for each individual *i* in the treatment group for which the counterfactual is being constructed .

As one of the results from the existing applied literature raises concerns about the sensitivity of the estimated impacts to particular matching approaches (e.g., Smith and Todd 2005), we generated estimates from alternative matching estimators including caliper and kernel matching. Likewise, we implement a cross-sectional version of these matching estimators by simply replacing the pre-post outcome measure with the post outcome measure.

7.1 Propensity Score Matching Estimates

In Table 8, we present the Average Treatment on the Treated (ATT) estimate of the effect of enrollment in an employer supported course on the growth in wages estimated over the pooled sample of men and women[11]. The propensity score matching is based on the characteristics of the sub-samples in the first wave of each panel. We report the Kernel based estimates which were generated using the Epanechnikov kernel function. We also carried out caliper matching results for most of our analysis with the caliper matching based on the size of 0.05 and 0.01. However, the Caliper-based estimates are very similar to the Kernel based estimates and so we report only the latter estimates in this report. In each case, the ATT estimate suggests that enrollment in at least one employer supported course over the panel period is associated with higher earnings growth over the panel period than is the case for not participating in an employer supported course with the estimates being 4.2 to 7.6 percent for men an between 7.1 to 7.4 percent for women. The estimates are smaller than what was found in Table 3 where no matching method is used indicating that some of the benefit in terms of wage growth to employer supported course enrollment in Table 3 is due to the selection into employer supported course enrollment. These matching estimates are consistent with recent evidence for Canada that shows

[11] In order to be able to compare the results of panel 4 with those from panel 5, both panel 4 and panel 5 have five years of longitudinal tracking in Table 8, while the panel 4 has six years of longitudinal tracking in Table A4 in the Appendix.

relatively small impacts for adult training after considering the endogeneity of the training decisions. For instance, Dostie and Leger (2007) and Dostie (2012) report wage premiums in the range of 1 to 3.5 percent for employer-sponsored training programs.

It should be noted that in our estimates presented in Table 8, we impose an empirical common support in the estimation of the propensity score matching method. In Appendix Table A7, we present the equivalent estimates without imposing common support. The estimates are very similar indicating that the distribution of covariates is somewhat similar between the treatment and control groups. In addition, we carried out Rosenbaum bounds tests for this model and present the relevant bounds in Appendix Table A8 and Table A9 for the full sample. The Rosenbaum test (2002) is used to assess if the estimates obtained using matching methods are robust to the possible presence of an unobserved confounder, which is the key assumption for matching based analyses. Rosenbaum's method should be thought of as a sensitivity analysis that relies on the sensitivity parameter gamma (Γ) which measures the degree of departure from random assignment of treatment. In a randomized experiment, randomization of the treatment ensures that Γ is equal to 1. In an observational study, where we do not have a randomized experiment, if Γ is equal to 2, and two subjects are identical on matched covariates then one might be twice as likely as the other to receive the treatment because they differ in terms of an unobserved covariate (Rosenbaum 2005).

Thus, the critical levels of Γ at which we would have to question our conclusion of positive effects are 1.34 and 1.36 for the full sample in Panels 4 and 5, respectively, before we reach the upper bound of significance level of 0.05. This implies that to attribute a higher wage due to an unobserved covariate rather than employer support course we would need to produce an about 34 percent to 36 percent increase in the odds of taking employer support courses, which we argue may be somewhat high to happen.

In Table 9, we carry out an additional matching estimation but instead of focusing on the change in the log wage as our dependent variable, we instead focus on the log wage of the respondents in the final wave of each panel[12]. Comparing cross-sectional matching impacts to difference-in-differences ones shed lights on the role of time-invariant unobserved factors in training decisions. For women, the cross-sectional ATT estimates are larger (than the log wage change estimates) for both panel 4 and 5 at 14.1 percent and 10.2 percent, respectively. This may indicate positive selection as more motivated or able workers are more prone to take part in training activities. The smaller impacts observed for the difference-in-differences matching approach simply reveal that once we control for time-invariant unobserved workers' characteristics training wage premiums decrease. For men, the differences between the Table 9 estimates and the Table 8 estimates are mixed with a small positive difference in panel 5 and a negative difference in panel 4, which do not indicate a positive selection into employer supported course enrollment. The estimates of Table 9 impose common support. In Appendix Table A5, we present the estimates where we do not impose common support. Comparing the estimates of Table A5 to Table 9 indicates that imposing common support does not have an important effect on the estimates. Also, in Appendix Table A8 and Table A9 we report the Rosenbaum bounds for this model for the case of men. The critical levels of Γ at which we would have to question

[12] In order to be able to compare the results of panel 4 with those from panel 5, both panel 4 and panel 5 have five years of longitudinal tracking in Table 9, while the panel 4 has six years of longitudinal tracking in Table A6 in the Appendix.

our conclusion of positive effects are 1.34 and 1.38 for the full sample in Panels 4 and 5, respectively. That is, an unobserved covariate should increase the odds ratio of participating in employer sponsored training by at least 34 percent to 38 percent in order to challenge our conclusions.

In the remaining analysis, we do not find that imposing common support leads to significant changes in our estimates (relative to those where we do not impose common support); therefore, in the remaining tables, we report only the estimates where we impose common support.

Next, we employ our matching method to evaluate whether there is a differential effect of employer supported course enrollment on the change in log wage rates for immigrants (especially recent immigrants) relative to the effect for the Canadian born population. In Table 10, we present ATT estimates on the impact of employer supported course enrollment on the change in the log wage rate for immigrants. In the panel 4 estimates, we see large and statistically significant estimates of 19 percent for men and 13 percent for women. However, the panel 4 estimates are not statistically significant for either men or women. In Table 11, we present the equivalent ATT estimates but for the case of recent immigrants defined as those in Canada for less than 10 years at the time of the first year of the panel. Each of the estimates is positive implying large impact of employer supported course enrollment but only the panel 4 estimate for men is significant at 31 percent and that is only at the 10 percent level of significance. Finally, the estimation was repeated again for the case of very recent immigrants (those with less than 5 years of residence in Canada). These immigrants likely face the greatest difficulty in terms of having their foreign credentials recognize and small investments in post migration human capital may have very large benefits if they lead to their pre-migration human capital credentials being recognized by Canadian employers. For men, this appears to be the case since the ATT is 28.3 percent in panel 5 and 40.2 percent in panel 4 and each of these estimates are statistically significant individually at the five percent level. For women the estimates are not significant.

Taken together, there appears to be evidence that at least for recent male immigrants, employer supported course enrollment has large effects on the log wage rate. However, more research on this topic is needed to better understand how robust these findings are. As was the case for returns to upgrades in formal education, it may be necessary to pool data from more than one SLID panel in order to generate sufficiently large numbers of observations in order to generate more precise estimates of these wage effects.

8. Impact of Employer Supported Course Enrollment on Social Outcomes

Our intention since the start of this project has been to analyze not only economic dimensions through which adult education and training might have impacts but to also analyze social dimensions. Unfortunately, we have found very few candidate variables in the SLID data that could be used to proxy for social outcomes. We have explored a number of possibilities and typically found that the data were not appropriate for the kind of analysis carried out in this study. For example, we planned to use the information on nutrition to see if employer supported course enrollment might have an impact on the healthy eating habits of the individuals taking these courses. However, this turned out to be infeasible since the questions were only asked beginning in 2009 and only for the province of Ontario.

It is possible to use the qualitative information on the respondent’s perception of his/her health status as a measure of a social outcome of interest to public policy. In the sub-section below, we discuss the method used to compare the health outcomes of respondents who participated in employer supported course enrollment to those who did not. We present results both without controlling for the endogeneity of the decision to participate in employer supported course enrollment and also using a propensity score matching method to account for the possible effects of this selection.

8.1 Health Status Effects of Employer Supported Course Enrollment

Due to the categorical nature of the health responses (excellent, very good, good, fair and poor), it was not possible to think of this as a continuous variable and use the kind of growth model employed in our wage analysis. Instead, we calculate a difference in proportions between those who reported a particular category of those who reported participating in employer supported training and all other respondents. While we do not carry out a multivariate model of the health status differences, we do include the full set of covariates that we have included in the wage growth models in the propensity score matching method which in this case is based on kernel matching. In the first part of our analysis, we do not condition on the initial (wave 1) health status of the person. As can be seen in Table 13[13], the estimated effects are typically not statistically significant with the exception of the “fair” category which is negative in both the panel 4 and the panel 5 estimates. This indicates that individuals who had employer support to

[13] See Table 13b for the relevant sample sizes for the untreated and treated samples for each of the panels.

enroll in a course were less likely to report having a “fair” health condition than were respondents who did not enroll in a course with employer support. While the other coefficients are not individually significant, there does appear to be a pattern in the point estimates which is consistent with higher probabilities of reporting better health status and lower probabilities of reporting poor health outcomes for those who were enrolled in an employer supported course. However, one possibility is that less healthy individuals may find it more difficult to participate in training. Since we do not include the initial health status as part of the propensity score matching method, it is possible that this effect is falling into the unobservables and generating a bias in the estimates of Table 13.

In order to investigate this possibility, we repeated the propensity score matching method after incorporating the health status in the first wave of the panel into the first stage matching method. The results are presented in Table 14. As can be seen, the estimates for the “Fair” case are no longer statistically significant. The coefficient on the “Very good” case for panel 5 is now significant and positive; however, the remaining coefficients are both close to zero and not individually statistically significant. Therefore, once we control for the initial health status of the person in the first wave of the panel, we see very little in the way of evidence and enrollment in course training has an impact on the health status of the individual.

Our analysis was extended by collapsing the “Excellent”, “Very Good” and “Good” categories into a single “Better” outcome and then collapsing the two remaining outcomes into a “Worse” health outcome then we defined an indicator variable based on these categories. This was then used in a propensity score matching method analogous to those used above to see whether enrollment in employer supported courses had the effect of raising the probability that a respondent identified their health as “Better” as opposed to “Worse”. In Table 15, we present the ATT estimate generated from an analogous econometric method to those employed in Tables 8-12. Unlike what was found in Table 14, we do see statistically significant ATT estimates indicating a 2.33 percent higher probability of the better health outcome for men in Panel 4 and a 2.59 percent higher probability of the better health outcomes for women in Panel 5. The other two ATT estimates of Table 15 are positive but not individually significant. Therefore, once we collapse the health outcome measure to create a binary outcome and once we apply the matching method, we do find some evidence of a positive relationship between employer supported course enrollment and self-reported health outcomes. However, our finding is not robust to the choice of panel. Clearly, this is an area warranting further research.

9. Placing Our Analysis within the Typology and Framework of the Adult Learning and Returns to Training Project

As already noted, this project is one part of a larger research program, the *Adult Learning and Returns to Training Project,* a multi-disciplinary research program. In this section, we compare the typology and analytical framework employed in our analysis to those described in the “Adult Learning Typology” (Myers, Conte and Rubenson, 2011) as well as the “Practical Guide to Understanding Returns to Training Investments: Adult Learning and Returns to Training Project” (Sweetman, Frenette, Myers and Voyer, 2011), developed as part of the larger research program. It is important to note that the Adult Learning Typology did not fit perfectly with the information available in the SLID surveys. There were a number of pieces of missing information (detailed below) which we would have used if available to create a better match between our analysis and both the Adult Learning Typology and the Analytical Framework. However, we did employ the concepts as much as possible.

We employed the definition of adult learning from the Adult Learning Typology: "... purposeful and directed learning undertaken by adults, either alone or in groups, to increase knowledge and skilled, and/or change behaviours, values, or beliefs" (p. 3, Myers, Conte and Rubenson, 2011). In addition, we restricted our attention to what can be thought of as prime age workers – those age 25-55 (which is virtually the same as the definition of prime working age adults described on page 4 of the Adult Learning typology) to allow us to focus on individuals who are likely to have a strong labour market attachment and have not yet reached the age where retirement is likely.

In terms of the five types of adult learning described in Section 3 of the Adult Learning Typology, our analysis of employer supported course enrollment best fits with the case of workplace-related learning which is defined as: "Related to one's current firm and supported at least to some extent by one's employer, but does not lead to a post-secondary credential and is not targeted to individuals with skills below Grade 12 level of IALS level 3" (p. 6, Myers, Conte and Rubenson, 2011).

Related to the Key dimensions of adult learning activities as described in Section 4 of the Adult Learning Typology, the following can be said. For the case of employer supported course enrollment, the Form is unclear since it could be formal, non-formal, informal or incidental; the

Provider is unclear since it could be provided by the firm or by an institution of higher learning; the Payer appears to be the employer but we cannot rule out the possibility that while the employer supports the course enrollment, the employee may also bear part of the cost; the Purpose of the course enrollment appears to be related to raising the employee's productivity with the firm given the fact that the course enrollment is supported by the employer; the Duration is relatively short, based on the sample means for hours in our data - 69 hours for women and 88 hours for men over the duration of the 6 year panel in Panel 4 (Table 1); the Design, Delivery, Instructor quality, and Credential are unclear based on the SLID questions.

The main part of our analysis had focused on measuring the benefits to workers of employer supported course enrollment. In addition, we have also investigated the benefits to upgrades in formal education credentials over the duration of the SLID panels. Considering each of these forms of adult learning, the employer supported course enrollment could be thought of as either Formal Learning or Non-Formal Learning as defined on page 2 of the Adult Learning Typology. It is unclear from the SLID questions whether the employer supported course enrollment is "structured and sequentially organized" making it more like formal learning or whether it represents course enrollment that is "not part of a formal educational program such as workshops, seminars, or guided/organized workplace training" as described in the adult learning typology. In terms of our secondary analysis of formal education upgrading (Table 7), it is clear that this represents Formal Learning under the Adult Learning Typology.

In terms of information that we would ideally liked to have known, and could be incorporated into future surveys, the following would have aided our analyses. First, for the case of employer supported course enrollment, it would have been helpful to know whether the employer was bearing the full cost of the course enrollment or whether this was shared with the employee. In addition, we would ideally want to know whether this form of adult learning was likely to only raise the worker's productivity at the firm (by increasing his/her firm specific human capital) or whether it was also raising the employee's productivity more generally at all firms (by increasing his/her general human capital). Additional information regarding the kinds of knowledge gained through the course enrollment would also have been beneficial for our analyses. For example, in the case of our analysis of the wage benefits to adult learning for immigrants, it would have been helpful to have known whether the employer supported course enrollment was specifically targeted at areas such as English or French language proficiency. Also, it would have been beneficial to have greater information on the number of employer supported courses taken each year. The SLID survey asks about whether at least one employer supported course was taken in each survey year as well as the total number of hours on all courses taken (without distinguishing between those with and without employer support). It would have been better to have known the number of employer supported courses taken each year and the number of hours spent on all employer supported courses each year.

Finally, it is important to place our current study within the set of types of analyses as described in the Practical Guide (Sweetman, Frenette, Myers and Voyer, 2011). As already noted, our analyses should not be thought of as a true cost-benefit analysis because we do not factor tuition costs directly into our analyses. These could be approximated for the case of the formal education analysis, but are unknown for the case of employer supported course enrollment.

In terms of the Hierarchy of Evidence of Table 1 in the Practical Guide, our project falls within the Middle Tier of studies. We do not have randomization of individuals into a treatment and control group, nor do we have a natural experiment to exploit. However, we do use the longitudinal nature of the SLID data along with a credible comparison group (those not enrolled in employer supported training in most of our analysis) to allow for the identification of the impact of the adult learning on outcomes such as wage rates and health outcomes through difference-in-differences estimation. In addition, we use propensity score matching to further investigate the sensitivity of our estimates to the validity of our comparison group.

10. Conclusions

A number of conclusions can be drawn from our research. First, probability of participation in employers supported course enrolment is lower for visible minorities than for non-visible minority workers. Also, probability of employer supported course enrollment is increasing with education.

In addition, we employed a difference-in-differences methodology in the estimation of the wage effects of employer supported course enrollment and investments mid career investments in formal education. Using the longitudinal nature of the SLID data, we find strong positive effects of employer supported course enrollment on wage growth. The estimated effect ranges from 6.8 to 7.7 percent for men and 7.5 to 9.3 percent for women. When we control for hours spent in education over the panel window for those enrolled in employer supported courses, we find a small but positive effect on wage growth for men but not for women.

The same exercise was carried out over sub-samples of less educated workers to see whether these course enrollment investments are especially beneficial for workers with less formal education. Using the: 1) high school diploma or lower education, and 2) the below university degree criteria to define sets of less skilled workers, we re-estimated our wage growth model. In each case, the estimated effects on wage growth of enrollment in employer supported course enrollment were similar to what was found in the estimation carried out over the sample of all workers.

We also estimated wage growth models related to increases in formal education (whether or not they were supported by the employer). In general, these estimates were not statistically significant, likely due to the small number of observations in the SLID panels who returned to complete formal education over the panel timeframe. However, the significant positive returns on the wage growth from the formal educational upgrade for males in panel 5 is consistent with the positive effects of participating in the employer supported training on the wage growth.

Propensity score matching was employed to account for potential biases not addressed through the parametric difference-in-differences method due to endogenous selection into employer supported course enrollment related to observable characteristics of the respondent. The average treatment effect on the treated estimates from the wage growth models were smaller in magnitude than the estimates generated ignoring the possible selection into employer supported course enrollment but were statistically significant and in the range of 4.2 to 7.6 percent for men and 7.1 to 7.4 percent for women.

We also carried out an investigation of whether there are differential returns to employer supported course enrollment for immigrants. These estimated differences coefficients on the interaction variables are in general positive but in most cases they are not statistically significant. Some evidence is found of higher returns for recent immigrant men implying 10.4 to 17.3 percent higher returns to employer supported course enrollment. However, we do not find this effect to be robust across panels of the SLID. We also employed our matching method to further investigate whether there are differential returns to course enrollment for recent immigrants. For recent immigrant men, the estimates are 28.3 percent in panel 5 and 40.2 percent in panel 4. For women the estimates are not significant. Given the magnitude of these estimates and the important role that post-migration investments in education and training are likely to play in the labour market adjustment of recent immigrants, this is an important area for future research, possibly involving new sources of data where a larger sample of recent immigrants is present.

The final part of our analysis involved a somewhat preliminary investigation into possible effects of employer supported course enrollment on non-economic outcomes. Due to data limitations, we focused on possible health impacts for the respondent. Using a propensity score matching method, we found some evidence of a positive relationship between employer supported course enrollment and self-reported health outcomes. However, our finding is not robust to the choice of panel. Clearly, this is an area warranting further research.

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Table 1: Weighted Sample Characteristics in first year of each SLID Panel by Gender

	Panel 4		Panel 5	
	Male	Female	Male	Female
Adult Education				
Employer-supported Course Enrollment	0.299 [2310]	0.269 [2277]	0.276 [2150]	0.244 [2089]
Employer-supported course enrolment intensity (in hours)	88.015 [2278]	69.435 [2259]	59.809 [2110]	46.728 [2057]
Education in first year of panel				
High School	0.162 [1072]	0.175 [1234]	0.152 [1065]	0.164 [1220]
Post-Secondary (no certificate)	0.128 [762]	0.119 [781]	0.130 [767]	0.126 [825]
Post-Secondary (with certificate)	0.350 [2315]	0.367 [2761]	0.370 [2361]	0.374 [2706]
Bachelor degree (only)	0.136 [723]	0.153 [968]	0.137 [737]	0.162 [1037]
Above Bachelor degree	0.076 [394]	0.054 [316]	0.076 [370]	0.057 [348]
Job characteristics				
Hourly wage rate	22.549 (11.627) [4931]	17.634 (9.324) [5087]	21.869 (11.828) [4993]	17.286 (9.545) [5247]
Tenure of job (in month)	136.080 [6409]	113.800 [6532]	134.481 [6398]	111.671 [6502]
Demographics				
Age	40.700 [7030]	40.814 [7623]	40.492 [6968]	40.403 [7474]
Visible Minority	0.142 [497]	0.147 [561]	0.161 [594]	0.170 [669]
Immigrant	0.207 [791]	0.222 [934]	0.198 [833]	0.216 [955]
Recent immigrant (<10 years)	0.063 [216]	0.066 [258]	0.056 [225]	0.074 [299]
Recent immigrant (<5 years)	0.033 [119]	0.039 [149]	0.033 [131]	0.042 [167]
Married	0.601 [4471]	0.609 [4890]	0.555 [4148]	0.588 [4601]
Total Observations	7030	7623	6968	7474

Note:

1. Weighted sub-sample size for each characteristics is presented in square brackets.(the sample mean is calculated by applying weights, but the sample size is the one without weights).
2. The statistical summaries are restricted to the population aged from 25 to 55 years old.

Table 2: Marginal Effects from Logit Estimation of Employer Supported Course Participation

COEFFICIENT	Panel 4		Panel 5	
	Male	Female	Male	Female
Age	-0.00999	0.0798**	0.0355	-0.00975
	0.037	0.037	0.044	0.043
Age Squared	-0.00001	-0.000943**	-0.00053	0.0000724
	0.00045	0.00044	0.00053	0.00053
Tenure	0.00405***	0.00514***	0.00461***	0.00530***
	0.00083	0.00086	0.0011	0.0011
Tenure Squared	-0.00000867***	-0.0000102***	-0.0000103***	-0.00000953***
	0.000002	0.000002	0.000003	0.0000028
Marital Status	0.188***	-0.0688	0.246***	-0.0489
	0.057	0.055	0.079	0.075
Visible Min	-0.357***	-0.336**	-0.315*	-0.488***
	0.13	0.14	0.16	0.17
Immigrant	-0.317***	-0.235**	-0.172	-0.376***
	0.11	0.11	0.13	0.14
High school	0.307***	0.760***	0.0836	0.987***
	0.11	0.14	0.15	0.22
PSE	0.605***	1.061***	0.673***	1.276***
	0.11	0.15	0.16	0.23
Certificate	0.706***	1.181***	0.709***	1.360***
	0.091	0.13	0.13	0.21
Bachelor	1.055***	1.681***	0.966***	1.597***
	0.11	0.14	0.15	0.22
Above	1.022***	1.657***	0.762***	1.838***
	0.13	0.16	0.18	0.24
Constant	-2.239***	-4.440***	-3.483***	-2.723***
	0.77	0.78	0.88	0.9
Observations	18359	17932	10167	9725

Note:

1. Additional Controls included for province, industry, firm size and occupation.
2. The default category for the education controls is the case of below a high school diploma.
3. Robust standard errors appear below the coefficient estimates.
4. ***denotes p-value <0.01, ** denotes p-value <0.05, and * denotes p-value <0.1.

The enrolment in the employer-supported course is available from 2002 to 2008.

Table 3: Change in log Wage Rates due to Enrollment in Employer Supported Courses-Short waves

COEFFICIENT	Panel 4		Panel 5	
	Male	Female	Male	Female
Enrolled in Course (With employer support)	0.068*** 0.02	0.093*** 0.02	0.077*** 0.02	0.075*** 0.02
Age	0.001 0.01	0.004 0.01	0.004 0.01	-0.008 0.01
Age Squared	-0.00003 0.0001	-0.000098 0.0001	-0.000077 0.0001	0.000062 0.0001
Tenure	-0.000089 0.0002	0.00018 0.0002	-0.000430* 0.0002	-0.00018 0.0003
Tenure Squared	0.0000003 0.0000006	0.0000002 0.0000005	0.00000115** 0.0000005	0.000000918* 0.000001
Marital Status	0.039** 0.02	0.0104 0.01	0.017 0.02	0.009 0.02
Visible Minority	-0.0548 0.04	0.021 0.03	-0.095** 0.04	-0.035 0.04
Immigrant	-2.77E-02 0.03	-0.058* 0.03	0.025 0.03	-0.032 0.03
High school	0.048* 0.03	0.036 0.03	0.046 0.03	0.093*** 0.03
PSE	0.0546* 0.03	0.0850*** 0.03	0.0978*** 0.03	0.133*** 0.04
Certificate	0.0901*** 0.02	0.0900*** 0.03	0.139*** 0.03	0.129*** 0.03
Bachelor	0.189*** 0.04	0.207*** 0.03	0.240*** 0.04	0.259*** 0.04
Above Bachelor	0.261*** 0.05	0.237*** 0.05	0.303*** 0.04	0.342*** 0.06
Constant	1.187*** 0.22	1.094*** 0.19	1.124*** 0.20	1.403*** 0.20
Observations R-squared	2963 0.20	3071 0.22	2915 0.27	2944 0.28

Note:

1. People in panel 4 are tracked from 2002 to 2006 for five years, which is the same as that in panel 5 where individuals are followed from 2005 to 2009 for five years.
2. Controls also included for province of residence, industry, occupation and the initial log wage.
3. The default category for the education controls is the case of below a high school diploma.
4. Robust standard errors appear below the coefficient estimates.
5. ***denotes p-value <0.01, ** denotes p-value <0.05, and * denotes p-value <0.1.

Table 4: Change in log Wages Rates due to intensity of courses supported by employer-short waves

COEFFICIENT	Panel 4		Panel 5	
	Male	Female	Male	Female
No. of Hours courses (with employer support)	0.000205*** 0.00006	0.00015 0.0001	0.000242*** 0.000076	0.000510*** 0.00014
Age	-0.0009 0.01	0.00459 0.01	0.00467 0.01	-0.00947 0.01
Age Squared	-0.000004 0.0001	-0.0001 0.0001	-0.000082 0.0001	0.000079 0.0001
Tenure	-0.00003 0.0002	0.0002 0.0002	-0.000432* 0.0002	-0.00013 0.0003
Tenure Squared	0.0000002 0.0000006	0.0000002 0.00005	0.00000118** 0.00000053	0.000001 0.000001
Marital Status	0.0397** 0.02	0.0122 0.02	0.0177 0.02	0.00794 0.02
Visible Minority	-0.0569 0.04	0.0209 0.03	-0.0953** 0.04	-0.0425 0.04
Immigrant	-0.0341 0.03	-0.0640** 0.03	0.0198 0.03	-0.0339 0.03
High school	0.0489* 0.03	0.0439* 0.03	0.0484* 0.03	0.0956*** 0.03
PSE	0.0557* 0.03	0.0967*** 0.03	0.107*** 0.03	0.140*** 0.04
Certificate	0.0985*** 0.02	0.107*** 0.03	0.151*** 0.03	0.134*** 0.03
Bachelor	0.203*** 0.04	0.234*** 0.03	0.253*** 0.04	0.262*** 0.04
Above Bachelor	0.267*** 0.05	0.263*** 0.05	0.311*** 0.04	0.345*** 0.06
Constant	1.228*** 0.22	1.074*** 0.19	1.105*** 0.20	1.437*** 0.20
Observations R-squared	2964 0.19	3075 0.20	2916 0.26	2947 0.28

Note:

1. People in panel 4 are tracked from 2002 to 2006 for five years, which is the same as that in panel 5 where individuals are followed from 2005 to 2009 for five years.
2. Controls are also included for province of residence, industry, occupation and the initial log wage.
3. The default category for the education controls is the case of below a high school diploma.
4. Robust standard errors appear below the coefficient estimates.
5. ***denotes p-value <0.01, ** denotes p-value <0.05, and * denotes p-value <0.1.

Table 5: Changes in log Wage Rates for Immigrants due to Employer Supported Course Enrolment

	Panel 4		Panel 5	
	Male	Female	Male	Female
Interaction of enrolment variable for immigrants				
Employer-supported course enrolment	0.0766*** (0.018)	0.0816*** (0.018)	0.0795*** (0.018)	0.0762*** (0.017)
Immigrant interaction	0.0497 (0.051)	0.102** (0.047)	-0.0111 (0.040)	-0.00736 (0.047)
Interaction of enrolment variable for immigrants in Canada for less than 10 years				
Employer-supported course enrolment	0.0823*** (0.017)	0.0931*** (0.018)	0.0721*** (0.017)	0.0768*** (0.016)
Recent immigrant (<10 years)	0.0172 (0.071)	0.0785 (0.073)	0.104** (0.051)	-0.0599 (0.079)
Interaction of enrolment variable for immigrants in Canada for less than 5 years				
Employer-supported course enrolment	0.0800*** (0.017)	0.0933*** (0.018)	0.0710*** (0.017)	0.0765*** (0.016)
Recent immigrant (<5 years)	0.108 (0.079)	0.112 (0.093)	0.173*** (0.057)	-0.0957 (0.11)

Note:

1. Controls are also included for education, age, job tenure, marital status, province of residence, industry, occupation, visible minority status, immigrant status and the initial log wage.
2. Robust standard errors appear below the coefficient estimates.
3. ***denotes p-value <0.01, ** denotes p-value <0.05, and * denotes p-value <0.1.

Table 6: Changes in log Wage Rate due to Course Enrollment with Employer Support: Less Skilled Workers-short waves

Population		Panel 4 Male	Panel 4 Female	Panel 5 Male	Panel 5 Female
High School Diploma or less	Coefficient	0.045*	0.058*	0.092***	0.122***
	std.err	0.03	0.02	0.03	0.03
	Observations	858	756	804	690
Less than a Bachelor degree	Coefficient	0.067***	0.086***	0.086***	0.085***
	std.err	0.02	0.02	0.018	0.017
	Observations	2369	2382	2315	2283

Note:

1. People in panel 4 are tracked from 2002 to 2006 for five years, which is the same as that in panel 5 where individuals are followed from 2005 to 2009 for five years.
2. Each row relates to a separate estimation over the sub-populations: a) those with a high school diploma or less education and b) those with education below the level of an undergraduate university degree.
3. Controls are also included for education, age, job tenure, marital status, province of residence, industry, occupation, visible minority status, immigrant status and the initial log wage.
4. Robust standard errors appear below the coefficient estimates.
5. ***denotes p-value <0.01, ** denotes p-value <0.05, and * denotes p-value <0.1.

Table 7: Changes in log Wage Rate due to an Upgrade of Formal Education

COEFFICIENT	Panel 4 Male	Panel 4 Female	Panel 5 Male	Panel 5 Female
Upgrade Dummy	-0.036	-0.0186	-0.071	0.092
	0.059	0.066	0.08	0.077
Upgrade from High School	0.0179	0.141*	0.178*	0.027
	0.08	0.082	0.095	0.098
Upgrade from PSE	0.0985	0.0924	0.186*	0.004
	0.084	0.1	0.10	0.10
Upgrade from Certificate	-0.00646	0.0872	0.249*	0.133
	0.13	0.1	0.14	0.095
Upgrade from Bachelor	0.0581	0.0937	0.182*	0.065
	0.083	0.08	0.10	0.11
Observations	2870	3011	2820	2890
R-squared	0.18	0.20	0.26	0.28

Note:

1. Panel 4 spans from 2002 to 2007, and Panel 5 spans from 2005 to 2010.
2. Controls are also included for education, age, job tenure, marital status, province of residence, industry, occupation, visible minority status, immigrant status and the initial log wage.
3. Robust standard errors appear below the coefficient estimates.
4. ***denotes p-value <0.01, ** denotes p-value <0.05, and * denotes p-value <0.1.

Table 8: Average Treatment Effect on the Treated for the impact of employer supported course enrollment on the Change in the log Wage Rate: Common Support-short waves

Matching Method	Treatment Result	Panel 4 Male	Female	Panel 5 Male	Female
Kernel	ATT	0.0420***	0.0740***	0.0764***	0.0712***
	Std.error	0.016	0.015	0.023	0.016
	Observations	2963	3071	2915	2944

Notes.

1. ***denotes p-value <0.01, ** denotes p-value <0.05, and * denotes p-value <0.1.
2. People in Panel 4 are tracked from 2002 to 2006 for five years, which is the same as that in Panel 5 where individuals are followed from 2005 to 2009 for five years.

Table 9: Average Treatment Effect on the Treated for the impact of employer supported course enrollment on the log Wage Rate at the end of the panel: Common Support – short waves

		Panel 4		Panel 5	
Matching Method	Treatment Result	Male	Female	Male	Female
Kernel	ATT	0.0308	0.141***	0.0902***	0.102***
	Std.error	0.022	0.021	0.025	0.020
	Observations	2963	3071	2915	2944

Notes.

1. ***denotes p-value <0.01, ** denotes p-value <0.05, and * denotes p-value <0.1.
2. People in Panel 4 are tracked from 2002 to 2006 for five years, which is the same as that in Panel 5 where individuals are followed from 2005 to 2009 for five years.

Table 10: Average Treatment Effect on the Treated for the impact of employer supported course enrollment on the Change in the log Wage Rate with Immigrant Interaction: Common Support

		Panel 4		Panel 5	
Matching Method	Treatment Result	Male	Female	Male	Female
Kernel	ATT	0.190**	0.130*	0.0665	-0.0278
	Std.error	0.088	0.068	0.041	0.062
	Observations	233	243	292	259

***denotes p-value <0.01, ** denotes p-value <0.05, and * denotes p-value <0.1.

Table 11: Average Treatment Effect on the Treated for the impact of employer supported course enrollment on the Change in the log Wage Rate with Recent Immigrant (<10 years) Interaction: Common Support

Matching Method	Treatment Result	Panel 4 Male	Panel 4 Female	Panel 5 Male	Panel 5 Female
Kernel	ATT	0.310*	0.18	0.103	0.128
	Std.error	0.17	0.16	0.093	0.18
	Observations	224	235	285	252

***denotes p-value <0.01, ** denotes p-value <0.05, and * denotes p-value <0.1.

Table 12: Average Treatment Effect on the Treated for the impact of employer supported course enrollment on the Change in the log Wage Rate with Recent Immigrant (<5 years) Interaction: Common Support

Matching Method	Treatment Result	Panel 4 Male	Panel 4 Female	Panel 5 Male	Panel 5 Female
Kernel	ATT	0.402**	0.194	0.283**	-0.0617
	Std.error	0.19	0.21	0.14	0.15
	Observations	224	235	246	206

***denotes p-value <0.01, ** denotes p-value <0.05, and * denotes p-value <0.1.

Table 13: Average Treatment Effect on the Treated of Employer Supported Course Enrollment on Proportional changes in health status:
Without controlling for selection based on the initial health condition

Health State	Treatment Effect	Panel 4 Coefficient	Bootstrap Std. Error	Panel 5 Coefficient	Bootstrap Std. Error
Excellent	ATT	0.0193	0.0136	0.0204	0.0142
Very Good	ATT	0.0033	0.016	0.019	0.0119
Good	ATT	0.0005	0.0122	-0.0163	0.0143
Fair	ATT	-0.0173**	0.0073	-0.019**	0.0078
Poor	ATT	-0.0057	0.0038	0.0041	0.0042

Note:

1. The results are obtained based on Kernel Matching.
2. ***denotes p-value <0.01, ** denotes p-value <0.05, and * denotes p-value <0.1.

Table 13b: Sample sizes of the Assignment used in Table 13

Assignment	Samples Panel 4	Samples Panel 5
Untreated	5,210	6,423
Treated	3,625	3,659
Total	8,835	10,082

Table 14: Average Treatment Effect on the Treated for Proportional changes on health status while controlling for selection based on initial health condition

State	Treatment Effect	Panel 4 Coef.	Bootstrap Std. Err.	Panel 5 Coef.	Bootstrap Std. Err.
Excellent	ATT	0.0071	0.0144	0.0022	0.0132
Very Good	ATT	0.0038	0.0153	0.0336*	0.018
Good	ATT	0.001	0.0159	-0.0221	0.014
Fair	ATT	-0.0129	0.0097	-0.0079	0.008
Poor	ATT	0.0008	0.004	-0.0057	0.004

Note:

1. The results are obtained based on Kernel Matching.
2. ***denotes p-value <0.01, ** denotes p-value <0.05, and * denotes p-value <0.1.

Table 15: Average Treatment Effect on the Treated for the effect of Employer Supported Course Enrollment on the Change in log Wage Rate due to Changes in Health Status: Common Support

Matching Method	Treatment Result	Panel 4 Male	Panel 4 Female	Panel 5 Male	Panel 5 Female
Kernel	ATT	0.0233**	0.0186	0.0103	0.0259*
	Std.error	-0.01	-0.014	-0.011	-0.015
	Observations	3831	3774	3757	3627

***denotes p-value <0.01, ** denotes p-value <0.05, and * denotes p-value <0.1.

Appendix

Table A1: Change in log Wage Rates due to Enrollment in Employer Supported Courses-long waves

COEFFICIENT	Panel 4	
	Male	Female
Enrolled in Course (with employer support)	0.0831*** 0.017	0.0952*** 0.018
Age	0.000602 0.011	0.00381 0.012
Age Squared	-0.000057 0.00013	-0.000095 0.00014
Tenure	0.000109 0.00026	-0.00028 0.00024
Tenure Squared	-0.00000008 0.0000008	0.0000001 0.000001
Marital Status	0.0478*** 0.018	0.0026 0.016
Visible Minority	-0.0537 0.044	0.0053 0.036
Immigrant	-0.0229 0.03	-0.0337 0.032
Course Enrollment	0.0831*** 0.017	0.0952*** 0.018
High school Dimploma	0.0501* 0.028	0.0473* 0.029
PSE	0.0650** 0.031	0.0929*** 0.032
Certificate	0.0874*** 0.022	0.0950*** 0.027
Bachelor	0.173*** 0.043	0.198*** 0.036
Above Bachelor	0.258*** 0.049	0.203*** 0.052
Constant	1.198*** 0.23	1.171*** 0.23
Observations R-squared	2869 0.19	3007 0.22

Note:

1. People in panel 4 are tracked from 2002 to 2007 for six years.
2. Controls are also included for province of residence, industry, occupation and the initial log wage.
3. The default category for the education controls is the case of below a high school diploma.
4. Robust standard errors appear below the coefficient estimates.
5. ***denotes p-value <0.01, ** denotes p-value <0.05, and * denotes p-value <0.1.

Table A2: Change in log Wages Rates due to intensity of courses supported by employer-long waves

	Panel 4	
	Male	Female
Hours on employer supported courses	0.000159*** 0.000046	0.000010 0.00015
Age	-0.00087 0.011	0.00447 0.012
Age Squared	-0.00004 0.00013	-0.0001 0.00014
Tenure	0.000171 0.00027	-0.00022 0.00024
Tenure Squared	-0.0000002 0.0000007	0.0000009 0.0000006
Marital Status	0.0513*** 0.019	0.00318 0.016
Visible Minority	-0.0597 0.046	0.00827 0.036
Immigrant	-0.0285 0.031	-0.0381 0.032
High School Diploma	0.0479* 0.028	0.0566** 0.029
Completed High School (Only)	--	--
Post-Secondary But no certificate	0.0628** 0.031	0.106*** 0.033
Certificate	0.0943*** 0.023	0.112*** 0.027
Bachelor	0.186*** 0.044	0.225*** 0.037
Above Bachelor	0.266*** 0.049	0.235*** 0.052
Constant	1.243*** 0.24	1.140*** 0.23
Observations R-squared	2870 0.18	3011 0.2

Note:

1. People in panel 4 are tracked from 2002 to 2007 for six years.
2. Controls are also included for province of residence, industry, occupation and the initial log wage.
3. The default category for the education controls is the case of below a high school diploma.
4. Robust standard errors appear below the coefficient estimates.
5. ***denotes p-value <0.01, ** denotes p-value <0.05, and * denotes p-value <0.1.

Table A3: Changes in log Wage Rate due to Course Enrollment with Employer Support:
Less Skilled Workers-long waves

Population		Panel 4 Male	Female
High School Diploma or less	Coefficient	0.0263	0.0395
	Standard error	0.028	0.029
	Observations	835	732
Less than a Bachelor degree	Coefficient	0.0829***	0.0879***
	standard error	0.018	0.019
	Observations	2301	2328

Note:

1. People in panel 4 are tracked from 2002 to 2007 for six years.
2. Each row relates to a separate estimation over the sub-populations: a) those with a high school diploma or less education and b) those with education below the level of an undergraduate university degree.
3. Controls are also included for education, age, job tenure, marital status, province of residence, industry, occupation, visible minority status, immigrant status and the initial log wage.
4. Robust standard errors appear below the coefficient estimates.
5. ***denotes p-value <0.01, ** denotes p-value <0.05, and * denotes p-value <0.1.

Table A4: Average Treatment Effect on the Treated for the impact of employer supported course enrollment on the Change in the log Wage Rate: Common Support-long waves

Matching Method	Treatment Result	Panel 4 Male	Female
Kernel	ATT	0.0564***	0.0767***
	Standard error	0.018	0.015
	Observations	2869	3007

Notes.

1. ***denotes p-value <0.01, ** denotes p-value <0.05, and * denotes p-value <0.1.
2. People in panel 4 are tracked from 2002 to 2007 for six years.

Table A5: Average Treatment Effect on the Treated for the impact of employer supported course enrollment on the Change in the log Wage Rate (non-common support)-long waves

		Panel 4		Panel 5	
Matching Method	Treatment Result	Male	Female	Male	Female
Kernel	ATT	0.042***	0.0768***	0.0764***	0.0685***
	Standard error	0.022	0.016	0.017	0.019
	Observations	2963	3071	2915	2944

Notes.

1. ***denotes p-value <0.01, ** denotes p-value <0.05, and * denotes p-value <0.1.
2. People in panel 4 are tracked from 2002 to 2006 for five years, which is the same as that in panel 5 where individuals are followed from 2005 to 2009 for five years.

Table A6: Average Treatment Effect on the Treated for the impact of employer supported course enrollment on the log Wage Rate at the end of the panel: Common Support-long waves

		Panel 4	
Matching Method	Treatment Result	Male	Female
Kernel	ATT	0.0430*	0.137***
	Standard error	0.024	0.02
	Observations	2869	3007

Notes.

1. ***denotes p-value <0.01, ** denotes p-value <0.05, and * denotes p-value <0.1.
2. People in panel 4 are tracked from 2002 to 2007 for six years.

Table A7 Average Treatment Effect on the Treated for the log Wage Rate at the end of the panel: Non-Common Support-short waves

		Panel 4		Panel 5	
Matching Method	Treatment Result	Male	Female	Male	Female
Kernel	ATT	0.0306	0.140***	0.0894***	0.105***
	Standard error	0.022	0.020	0.023	0.020
	Observations	2963	3071	2915	2944

Notes.

1. ***denotes p-value <0.01, ** denotes p-value <0.05, and * denotes p-value <0.1.
2. People in panel 4 are tracked from 2002 to 2006 for five years, which is the same as that in panel 5 where individuals are followed from 2005 to 2009 for five years.

Table A8: Rosenbaum bounds for two benchmark models from Panel 4-short waves

Gamma	sig+	sig-	t-hat+	t-hat-	CI+	CI-
Diff-in-Diff model for Log Wage: Enrollment in Employer Supported Courses						
1	1.30E-13	1.3E-13	0.047046	0.047046	0.034394	0.059809
1.1	3.00E-07	0	0.03202	0.062204	0.019475	0.07511
1.2	0.001991	0	0.018462	0.076172	0.005927	0.089338
1.24	0.018472	0	0.013362	0.081469	0.00081	0.09472
1.25	0.029236	0	0.012115	0.082781	-0.00044	0.096042
Diff model for Log Wage: Enrollment in Employer Supported Courses						
1	0	0	0.087013	0.087013	0.068185	0.105809
1.1	1.80E-11	0	0.064636	0.109332	0.0457	0.128248
1.2	3.10E-06	0	0.044168	0.129788	0.025141	0.148683
1.3	0.004783	0	0.025342	0.148488	0.006238	0.16737
1.34	3.13E-02	0	0.018169	0.155517	-0.00097	0.174479

Table A9: Rosenbaum bounds for two benchmark models from Panel 5-short waves

Gamma	sig+	sig-	t-hat+	t-hat-	CI+	CI-
Diff-in-Diff model for Log Wage: Enrollment in Employer Supported Courses						
1	1.1e-16	1.1e-16	0.058271	0.058271	0.044433	0.072185
1.1	1.4e-09	0	0.041693	0.074918	0.027994	0.089064
1.2	.000067	0	0.026752	0.090335	0.013046	0.104692
1.3	.019655	0	0.014382	0.103285	0.000711	0.117809
1.36	.030518	0	0.013079	0.104662	-0.00062	0.119193
Diff model for Log Wage: Enrollment in Employer Supported Courses						
1	0	0	0.09267	0.09267	0.074243	0.111161
1.1	6.30E-14	0	0.070572	0.114806	0.052146	0.133467
1.2	6.10E-08	0	0.050499	0.135114	0.031944	0.153673
1.3	0.000405	0	0.031988	0.153632	0.013394	0.172309
1.38	0.028381	0	0.018194	0.167513	-0.00053	0.186268

Note:

1. People in panel 4 are tracked from 2002 to 2006 for five years, which is the same as that in panel 5 where individuals are followed from 2005 to 2009 for five years.
2. gamma - log odds of differential assignment due to unobserved factors
3. sig+ - upper bound significance level
4. sig- - lower bound significance level
5. t-hat+ - upper bound Hodges-Lehmann point estimate
6. t-hat- - lower bound Hodges-Lehmann point estimate
7. CI+ - upper bound confidence interval (a= .95)
8. CI- - lower bound confidence interval (a= .95)