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Return to Education for Australian Male Workers: An estimate with HILDA

Peng Yu

(PhD candidate)

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Contents

Abstract

This essay is trying to contribute some new ideas to estimating the return to education in Australia. First, it is based on HILDA, providing an up-to-date estimate. Second, it not only tries different methods (OLS IV and proxy), but also uses different specifications with different sets of explanatory variables. Third, it uses partner's education as instrument for schooling. Fourth, it uses the self-assessed job complex level and job stress level jointly as proxy for working ability for the first time. It finds that the return to education is not constant for all education level, and the estimate is more sensitive to the number and kinds of explanatory variables in the model than to the methods used. A comparably reliable estimate for the average rate of return to schooling for the married male full-time workers is about 6.7 percent.

1. Introduction

In the last two decades Australian education (especially higher education) has undergone great changes to its structures and funding, and quite likely the changes will continue. The main objectives of this essay are to use recent data to provide a more reliable estimate of the return to education in Australia, and to discuss the risk implications of the dispersion in the return to education. Hopefully it will provide some useful background information for the discussion on the rationality of the reforms.

Estimating return to education is not new, but unobserved heterogeneity makes it still a challenging problem. Most researchers rely on one method or another to tackle the problem. This essay tries to contribute several new ideas to the issue. First, based on a recent survey, the first wave of HILDA[1], it provides an up-to-date estimate of the return to education. Second, it not only tries different methods (OLS, IV and proxy), but also uses different specifications with different sets of explanatory variables. Third, it uses partner's education as instrument for schooling. Fourth, it uses the self-assessed job complex level and job stress level jointly as proxy for working ability for the first time.

Not surprisingly, the results show that the estimated rates of return to education are different when different models and methods are used. The rates are more sensitive to the number and kinds of explanatory variables in the model. In a commonly used linear schooling model with only schooling, experience and tenure, the rate of return to education is about 6.6-8.3 precent by different methods (OLS IV or Proxy). When industry and occupation as well as some other explanatory variables are included, the coefficient drops to less than 5 percent. Another important finding is that the marginal rate of return to education is not constant but increasing by schooling.

[1] The Household, Income and Labour Dynamics in Australia.

The following section is literature review. Sections three to six introduce the data set (first wave of HILDA), the sample, the variables and the methods. Section seven gives a detailed report and analyses on the results of estimations. Section nine is conclusion.

2. Survey of literature

Why people attend more education? Economists believe that higher economic return is the key concern. Human capital theory argues that education raises labour's productivity and thus leads to higher wage offer (Schultz 1961, 1961a). The Screening theory, however, argues that high-ability workers obtain more schooling simply because more schooling labels them as "more productive" (Spence 1973; Stiglitz 1975). Nevertheless, it also agrees that workers with more education tend to have higher wages. Blaug (1972, p. 54) even claims that, "The universality of this positive association between education and earnings is one of the most striking findings of modern social science."

It is not difficult to find the positive correlation between wage and years of schooling, but it is not easy to pursue the *precise* rate of return to education. Both human capital theory and screening theory find positive correlation between schooling and ability. People with longer schooling get higher earning at least in part due to their unobserved ability and motivation; therefore, the estimate of the return to education by conventional earnings function tends to be biased. This is the most challenging problem in estimating the return to education.

People have tried many methods to solve this problem. Below are discussed four of them.

The first one is using panel data (for example, Angrist and Newey 1991). By first differencing (FD) or fixed effects (FE) method we can eliminate the unobservable heterogeneities like ability and family backgrounds. One problem is that it is difficult to obtain appropriate panel data, and usually the time span of the available panel data is not long enough. Consequently, few changes can be observed in schooling, and experience changes the same for most people in the sample. FD and FE do not work well in that case.

A variation of the panel data method is using samples of identical twins (for example, Ashenfelter and Krueger 1994, Ashenfelter and Rouse 1998, and Behrman *et al* 1980). The twins are supposed to have similar ability and similar family background, so the unobserved ability and family background factors can be eliminated by differencing across twins. One problem for this approach is that whether the twins' abilities are similar enough and their wages and educations are different enough to make first differencing method appropriate. Another problem is whether the twins can be seen as a random sample from the population if our key interest is in the population return.

IV method is among the most popular methods of removing the endogeneity of schooling. However, it is very difficult to find valid instruments. Well-known instruments for schooling include quarter of birth (Angrist and Krueger 1991), Vietnam-era draft lottery (Angrist and Krueger 1992), siblings' sex (Butcher and Case 1994), whether grew up near a four-year college (Card 1995), and rank-order instrument (Rummery *et al* 1999). Rummery *et al* (1999) use the 1985 wave of the Australian Longitudinal Survey to estimate return to education for Australian youth, and find a return of about 8 percent.

Another way is the proxy method (also known as plug-in solution to omitted variables) (for example, Griliches and Mason 1972, Blackburn and Neumark 1992, 1993, and 1995). Commonly used proxies for ability are various kinds of test scores, such as IQ and KWW[2]. The problem is whether the proxy is valid. "If test scores are actually unrelated to ability, or (more plausibly) if the unobserved ability that is rewarded in the labour market differs from the ability leading to higher test scores", the result by this method will be problematic (Blackburn and Neumark 1992, p1424).

[2] Knowledge of the world of work.

As can be seen, these researches all contain some useful ideas as well as some shortcomings. In this research, to estimate the current rate of return to education in Australia, we will try to learn from these relevant literatures and will do something different.

3. The Data

The data set we used is the first wave of HILDA in 2002. There are 13,969 individuals and 7,682 households in the survey, and it has many variables concerning household structure, family background, education, employment history, current employment, job search, income, health and well-being, etc[3].

4. The Sample

For the sake of using partner's schooling as instrument of schooling and decreasing potential measurement errors, we mainly use the sub-sample of the married[4] male workers who are aged between 15-65, have only one-job and are working full-time, and omit the observations with missing values. At last we have about 2,060 valid observations. Among them, about 10.2 percent have postgraduate degree or certificate, about 14.5 percent have a bachelor degree, 9.8 percent have a diploma, and 36.6 percent have some kind of certificate.

5. The Variables

The two key variables in our models are hourly wage and years of schooling, while HILDA doesn't collect the information, so we have to derive them from the relevant variables in HILDA. Concerning wages and salary, HILDA has many variables (including derived ones). To make the calculation simple and consistent (maybe not the best), we choose the derived variable AWSCMG in HILDA (ie, Gross wages & salary per annum – current – main job) as annual wage. Then we divide AWSCMG by (52*AJBHRU) to get hourly wage. The question for AJBHRU in HILDA questionnaire is: Including any paid or unpaid overtime, how many hours per week do you usually work in all your jobs? . The average wage in the sub-sample we use is A$53,421.2 per annum, and the average hourly wage is A$22.

As for years of schooling, we mainly use AEDHIGH and AEDHISTS to recover it. In HILDA survey AEDHIGH is a derived variable telling the highest education level achieved, and AEDHISTS is the highest year of school completed or currently attending. For degree/certificate holders, we use AEDHIGH to generate years of schooling. In HILDA, AEDHIGH has 10 categories: postgrad – masters or doctorate; grad diploma, grad certificate; bachelor, adv diploma, diploma; cert III or IV; cert I or II; cert not defined; yr12; yr11 and below; undetermined. Accordingly, the value of years of schooling is set 18 for people with master degree or doctorate; for people with graduate diploma or graduate certificate the value of years of schooling is set 17, for people with bachelor degree their years of schooling will be 16, for people with advanced diploma or diploma the value is 14, and for people with certificate the value is set 13. For people with no degrees, diploma or certificates, in other words, for school leavers, we use AEDHISTS to generate their years of schooling. Defined in this way, the variable 'years of schooling' only reflects the highest education level achieved, which is the socially recognised years of schooling, having nothing to do with the years the people actually take to achieve the education level. Thus the people spend unnecessarily longer time to achieve a certain level

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[3] For more information about HILDA, please refer to the website of www.melbourneinstitute.com.
[4] Including married and *de facto*.

of education are penalised in our model. In our sample the average year of schooling is about 13 years.

We also derive some other variables used in our models, including variable for experience[5], four education dummy variables, eight industrial dummy variables and six occupational dummy variables. In order to balance the observations within each category and decrease the number of dummy variables, we combine some industrial as well as occupational categories together. For instance, we combine agriculture (A in ABS industrial classification) and fishing and mining industries (B in ABS industrial classification) into one category, denoted by dummy variable ind1. Since the key variable we are interested in is years of schooling, and we don't care too much about the coefficients of industry and occupation, it is not a big problem however we combine the industrial and occupational categories. Table 1 gives the definitions and statistical summary of the main variables. Hereafter we will use the variable names directly.

6. The Analyses

To estimate the return to education, we start with OLS. The baseline model is the one with lhwage (log hourly wage) as the dependent variable, and schooling, exper, exper2, tenure and tenure2 as explanatory variables. Then we increase the explanatory variables set by set. The first extension is adding English (for English ability), health and union dummies, the second extension is adding industry dummies, and the third extension is adding occupation dummies.

Then, IV method is used, with pschooling (partner's schooling) as instrument for schooling. Proxy method is also applied. Since there are no IQ or similar test-scores in

[5] In HILDA there is a potential variable for experience, years in paid work, while we choose to derive it by formula: exper = age – schooling – 5. We have tried models with these two experience variables, the estimates for schooling are almost the same. The coefficients for experience are quite different, while it doesn't matter much as they are not our key concern.

HILDA, jcomplx and jstress[6] are used instead. The validity of the instruments and the proxies is to be discussed later. The results from different methods are compared to show whether they are very different from each other.

7. Estimating the rate of return to education

7.1 OLS method.

In the baseline model the explanatory variables include schooling, exper, exper2, tenure and tenure2 (results are listed in Table 2). All variables are significant at one percent level except tenure2, which is jointly significant with tenure at one percent level. The rate of return to schooling is about 7.3 percent. When several dummies for English ability, health and union are added in the model, the coefficient of schooling is hardly changed, while it drops to 6.3percent when industry dummies are added, and further to five percent when occupation dummies are also added. That means the return to schooling is heavily influenced by industry and occupation. In the mean time, the adjusted R^2 keeps increasing, indicating that including more explanatory variables is slightly preferable.[7]

Evidence for functional misspecification has been found by RESET[8], so the marginal rate of return to schooling is not constant. Two other kinds of models are estimated, both of which passed RESET. One is including quadratic and cubic schooling apart from

[6] The question asked in the HILDA questionnaire concerning jcomplx is that indicating how strongly you agree or disagree with "my job is complex and difficult". The relevant question for jstress is that "my job is more stressful than I had ever imagined". There are seven degrees from 1 (strongly disagree) to 7 (strongly agree) for both of them.

[7] It is always controversial whether we should include more variables in the model (see Wooldridge 2000, pp196-197 for a discussion).

[8] What we use is Ramsey's (1969) regression specification error test: first, regress lhwage with schooling and other variables; second, predict the fitted value of lhwage (lhwagehat), and calculate lhwagehat^2 and lhwagehat^3; third, regress lhwage with the original model augmented with lhwagehat^2 and lhwagehat^3; last, test the joint significance of lhwagehat^2 and lhwagehat^3. If significant, then there exists functional misspecification (see Wooldridge 2000, pp281-282).

schooling; the other one is using four education dummy variables, postgrad, bachelor, diploma, and certific.

In the former one, the marginal rate of return to education is increasing by years of schooling. Holding experience and tenure constant, the marginal return to an extra year of schooling for a person having 13 years of schooling (sample average) is 6.76 percent. In the latter model, also holding experience and tenure constant, compared with a person with no more than 12 years of education, on average a postgraduate earns 47.3 percent more, a bachelor-degree holder earns 39.3 percent more, a person with diploma earns 22.8 percent more, while the hourly wage of a certificate holder is not significantly different[9].

Once again, as more explanatory variables are included, the estimated returns to education are changing in both kinds of models. In the models with schooling, schooling2 and schooling3, the estimated marginal rates of return at certain level of education are quite sensitive to the accuracy of the coefficients; unfortunately, we can hardly get accurate estimates of them (the standard errors of these coefficients are fairly large). However, we find consistently that the marginal rate of return is increasing by schooling. (See Table 2 for detailed results)

In the mean time, we find that on average people with poor health earn 26-31 percent less and union members earn 11-15 percent more than the others. Both of the effects are significant at one percent level. However, English dummy has a positive but not significant effect on wage (maybe because more than 98 percent of the sample speak English well).

Breusch-Pagan tests show evidence of heteroskedasticity in all these models (White tests also show existence of heteroskedasticity in most cases), so we use robust option in the regressions to correct the standard errors.

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[9] One reason may be that we put all people with different kinds of certificates, including certificate i, ii, iii, iv and other undefined ones, into one category of certificate.

7.2 IV method.

The OLS estimates can be biased in the presence of endogeneity of schooling. To tackle with this problem, we have tried IV method. The instrument we use for schooling is partner's schooling (pschooling). Few, if any, reference has been found of using this instrument. Its validity may be questioned. Perhaps the most serious attack is that able people tend to marry with able people and education is signalling one's ability, so partner's education may be correlated with one's own ability (in the residual). This is a problem but maybe not a big one. First, criteria for a good partner are different from those for a good employee. Men good at courting ladies are not necessarily good employees. And, working ability is not necessarily as important for being a good wife as for being a good husband. Second, in the "marriage market" a female's education is more likely to be used as a signalling device for a certain life style, way of behaviour, and social status, rather than for her ability. Therefore, the potential correlation between one's ability and his partner's schooling is possibly much smaller than that between one's ability and his own schooling. Third, since partner's schooling is hardly a determinant in one's wage, it can be excluded from the earnings function. In addition, by regressing schooling on the instrument variable pschooling and all other exogenous variables, we can establish that cov(schooling, pschooling) $\neq$ 0.

From the above arguments and tests, there is some confidence concerning the validity of the instrument. Nevertheless, if the partner's schooling is truly a poor instrument for schooling, we may expect a bias for the IV estimates equal to

$$[\text{corr}(\text{pschooling, ability})/\text{corr}(\text{pschooling, schooling})] * [\sigma_{\text{ability}} / \sigma_{\text{schooling}}].$$

As partner's schooling is positively correlated with one's own schooling, if it is also correlated with one's ability (more likely positive in the common sense), then the return to schooling will probably be overestimated by IV method.

By IV method, as shown in Table 3, the estimated coefficient for schooling in the baseline model is 8.3 percent, one percentage point higher than the corresponding[10] OLS estimate (7.3 percent). After controlling English, health and union variables, the coefficient rises slightly to 8.4 percent, while when industry and occupation dummies are successively included in the model, it drops to 6.9 percent and further to 4.9 percent, in comparison with 6.3 percent and five percent by the corresponding OLS method. So in that case it is not clear whether omitted ability causes positive or negative bias in OLS.

7.3 Proxy method.

As mentioned above, various test scores are commonly used as proxies for ability. This essay uses jcomplx and jstress jointly as proxy of working ability for the first time. Jcomplx is the self-assessed job complex/ difficult level. Justification for using jcomplx as proxy for ability is that generally more complex job demands higher ability. We find that there is significant positive correlation between jcomplx and hourly wage no matter which and how many other variables are controlled. One critique is that jcomplx itself may be a necessary part of the earnings function because employers would like to pay more for more complicated work. But in our case it is not necessarily valid because we are talking about hourly wage.

Given a complicated job, generally there are three possibility for the less able person: one is simply that he cannot do it, the second is that he can do it but with longer time, and the third is that he tries to do it in the given time as for the able person but feels more stressful. In the first case he will not take the job. In the second a rational employer will be reluctant to pay him a higher hourly wage because he do it in longer time and/or with lower quality. So a more complicated job not necessarily leads to higher hourly wage, but given the same complicated job, a higher hourly wage is more likely due to higher ability.

[10] The term, “corresponding”, here means that the estimates are from models with the same explanatory

Considering the third case, luckily we have a variable for the self-assessed job stress level in HILDA, ie, jstress. It alone is not significant in the earnings function, while it will be significant after controlling jcomplex, and the sign of it is consistently negative in all the cases. So it is more likely that jstress reflects somewhat one's working ability rather than that it reflects the real stress level of the job[11].

In short, jcomplx and jstress both reflect some aspects of one's working ability, so it may be a good idea to plug them simultaneously into the earnings function jointly as proxy for ability. The idea is that more complicated job demands higher ability, while given the job of similar complex level the less able people tend to feel more stressful.

After controlling the variables of experience and tenure, the coefficient of schooling is about 6.6 percent. The coefficients of jcomplx and jstress are 0.027 and –0.02 respectively. They are all significant at one percent level[12]. Once again, if industry and occupation are also controlled, the coefficient of schooling will drop to 4.7 percent. (All results for proxy method are listed in Table 4)

Again, all of the non-linear schooling models show increasing marginal return to schooling. For a person with about 13 years of schooling (the sample average), the estimated marginal rates of return to schooling are between 7.5 percent and 4.6 percent depending which else variables are also controlled in the model.

Using models with four education dummies, the coefficients of the four education dummies by proxy method are all lower than those estimated by OLS method.

Interestingly, after controlling jcomplx and jstress (proxy for ability), speaking English well significantly increases one's hourly wage by about 21.7 percent to 27.1 percent,

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variables but by different methods.

[11] If jstress reflects the real stress level of the job, as higher job stress demands more compensation, then it should have a positive sign in the earnings function. Obviously it is not the case here.

[12] I've also tried to use jstress as instrument of jcomplex, in the mean time using exp as instrument of exper, and found that the coefficient of schooling is (and those of education dummies in another model are) slightly higher than OLS (see columns 5, and 9-13 of Table 5 for details).

while the effect of health is not significant anymore. Now union members on average still earn significantly 10-14.4 percent more than non union members.

By Breusch-Pagan test, we have found evidence for heteroskedasticty, so we use robust option in all regressions and thus the inferences are basically valid.

7.4 Selection biases.

Apart from endogeneity of schooling and heteroskedasticity, selection bias can also be a problem. Potentially, there are two kinds of selection bias in our models. One is for using only married male (more able people are more likely to be married); the other one is due to using only the working male (wage offers for those not working are not observed);

Concerning the first kind of bias, we have tried to compare the results of using full male sample with those of using the sub-sample of married males by OLS. The coefficients of schooling are very similar (for models OLS1-1, OLS2-1, OLS3-1 and OLS4-1, using full male sample the coefficients of schooling are 0.073, 0.073, 0.063 and 0.047 respectively, in comparison with 0.073, 0.074, 0.063 and 0.050 of using only married males). So it seems to be a trivial problem.

Concerning the second kind of bias, Heckman correction (Heckman 1977, 1979) provides a solution. However, since there also exist endogeneity problems when estimating the inverse Mills ratio and there is no valid instrument in the bigger sample, it is not clear whether Heckman correction will make things better or worse. So we have not done any correction, while surely it is an issue for further investigation.

7.5 Rethinking about the model.

After trying for all these methods, we can get some firm conclusions: first, the marginal rate of return to schooling is not constant, but increasing by schooling (a little bit surprisingly); second, the coefficient of schooling tends to drop as more explanatory variables are included in the model; third, in Australia among the full-time male workers, union members on average earn at least 10% more than non-union members, given all other factors the same. However, we still cannot get an accurate estimate of the rate of return to schooling because it varies by methods (OLS, IV or Proxy) as well as by models with different sets of explanatory variables. And we can hardly say which one of the estimates is more reliable because each of them has some weaknesses.

This leads to a deep question: which variables should appear at the right hand side of the earnings function? Fundamentally, wage is decided by productivity of labour, which has several basic determinants, including knowledge, skill, ability and opportunity. Knowledge is accumulated by studying, and formal education is the main channel. Skill is gained through training and learning by doing, and working experience is its main source. Ability is usually viewed as innate and does not change over time. The productivity of labour is different at different position and different environment. Not every body can find the most-fitted job and maximise its potential productivity. We use opportunity to cover all the factors influencing fulfilment of productivity (like social norms, network, incentive and luck). Unfortunately, most, if not all of these determinants are unobservable in reality. We have to use proxies. Almost universally schooling is used as proxy for knowledge and working experience as proxy for skill. Test scores like IQ are popular candidates of proxy for ability, while opportunity does not have any commonly used proxy. Even the four basic determinants of wage are hardly exclusively independent, let alone these proxies. This inevitably causes problems in estimation.

The next question is what we really mean by rate of return to schooling. Formal educational institution is a place for studying and accumulating knowledge, which makes people more productive. In that sense schooling can act as a proxy for knowledge. But in fact return to schooling is more than that. Through formal education, especially higher education, people can also improve their skills, and more importantly, can get familiar with the social norms, form their network, enhance self-confidence, and thus will be at a better position to maximise their potential productivity. So return to schooling should be much higher than the return to knowledge accumulated by one more year of schooling (with schooling as proxy). The problem is that we cannot tell exactly how much higher it will be. A following question is that: when estimating the rate of return to schooling, what is the key concern of people, the rate of return to schooling itself or that to the accumulated knowledge by one more year of schooling? If we view education as an investment, apparently the former is more appropriate.

If these arguments hold water, then in the model each explanatory variable should have a clear role (ie, acting as a proxy for one of the unobservable basic determinants), and if possible all these variables should be included. In addition, all other explanatory variables should not be significantly influenced by schooling, otherwise the return to schooling will be partly taken away and thus it will be underestimated.

Following this logic, apart from schooling variables, we should include in the model exper, exper2, tenure and tenure2 (as proxy for skill), and jstress and jcomplx (as proxy for ability). English, health and union influence the maximisation of labour's productivity, and can be viewed as proxies for opportunity factors. And they are not significantly influenced by schooling, so they should also be included in the model. While industrial and occupational dummies don't have a clear role in our framework and they are significantly influenced by schooling, excluding them may be appropriate although they have a significant effect on wage.

In that case, proxy models P2-1, P2-2 and P2-3 (Table 4) may be the most appropriate. Model P2-1 shows on average the rate of return to schooling is about 6.7 percent, while Model P2-2 tells us that the marginal rate of return to schooling is increasing, and for a person with 13 years of schooling (the sample average) it is about 6.8 percent. The results are not very different. So we may conclude that the average rate of return to schooling for Australian male full-time workers is about 6.7 percent. Model P2-3 shows that given all other factors the same, on average people with postgraduate degrees, people with bachelor degrees and people with diploma respectively earn 47.3 percent, 40.5 percent and 22.6 percent more than people having no higher education, while the difference between the wage of certificate holders and that of the school leavers is not significant.

8. Conclusion

The essay has estimated the return to education with the recent survey (HILDA) in Australia. It differs from other researches in this area in several ways. First, it estimates the return to education by different methods (including OLS, IV and Proxy), as well as with different functional specifications and increasing numbers of explanatory variables. Second, it uses partner's schooling as instrument for schooling after discussing its validity. Third, self-assessed job complex and job stress levels are jointly used as proxy for working ability for the first time. In addition, various kinds of tests have been employed to support the estimates. It finds that the coefficient of schooling is more sensitive to the number and kinds of explanatory variables included in the model than to the methods used, and the marginal rate of return is increasing by schooling. It claims that in the earnings function all explanatory variables act as proxy for some of the unobservable fundamental determinants of productivity, including knowledge, skill, ability and opportunity. However, since the real concern of people is the return to schooling itself rather than return to the accumulated knowledge by one more year of schooling, all explanatory variable with a clear role in the earning function should be controlled except those which are significantly influenced by schooling. The estimated average rate of return to schooling for Australian male full-time workers is about 6.7 percent.

9. Tables

Table 1: Summary of Variables

Variables	Descriptions	Mean	Std. Dev.
wage	Gross wages & salary per annum –current –main job (A$)	53421.2 (obs. 2064)	31619.91
lwage	Log wage	10.75 (obs. 2064)	.51
hwage	Hourly wage (A$) = annual wage /(52*weekly working hours)	21.99 (obs. 2063)	11.90
lhwage	Log hourly wage	2.97 (obs. 2062)	.50
schooling	Equivalent years of highest education	13.23 (obs. 2064)	2.45
schooling2	schooling squared	181.08 (obs. 2064)	64.60
schooling3	cubic schooling	2552.76 (obs. 2064)	1338.67
pschooling	Partner's schooling	12.98 (obs. 1986)	2.53
postgrad	Takes 1 if highest education level is bachelor or above, and 0 if otherwise	.1017 (obs. 2064)	.3024
bachelor	Takes 1 if highest education level is bachelor, and 0 if otherwise	.1453 (obs. 2064)	.3525
diploma	Takes 1 if highest education level is diploma, and 0 if otherwise	.0983 (obs. 2064)	.2979
certific	Takes 1 if highest education level is certificate, and 0 if otherwise	.3658 (obs. 2064)	.4818
exper	Years of experience = age – schooling –5	22.63 (obs. 2062)	10.37
exper2	exper squared	619.51 (obs. 2062)	515.86
exp	Years in paid work	20.89 (obs. 2063)	12.27
exp2	exp squared	586.9 (obs. 2063)	552.74
tenure	Years with current employer	8.61 (obs. 2063)	8.75
tenure2	tenure squared	150.77 (obs. 2063)	271.21
jstress	Self-assessed job stress level (1-7). Takes 1 if strongly disagree with the claim that my job is more stressful than I had ever imagined, and 7 if strongly agree	3.62 (obs. 1909)	1.71
jcomplx	Self-assessed job complex level (1-7).). Takes 1 if strongly disagree with the claim that my job is complex and difficult, and 7 if strongly agree	4.43 (obs. 1908)	1.81
English	Takes 1 if speaking English well, and 0 if otherwise	.987 (obs. 2064)	.11
health	Takes 1 if health is fair or better, and 0 if health is poor	.99 (obs. 2061)	.098
union	Takes 1 if being trade union member, and 0 if otherwise	.344 (obs. 2064)	.48

ind1	Takes 1 for being in agriculture, or fishing and mining industries (A & B in ABS industrial classification), and 0 if otherwise	.078 (obs. 2057)	.27
ind2	Takes 1 if in manufacturing industries (C in ABS classification), and 0 if otherwise	.17 (obs. 2064)	.38
ind3	Takes 1 if in electricity, gas, water supply or construction industries (D & E in ABS classification), and 0 if otherwise	.13 (obs. 2064)	.33
ind4	Takes 1 if in wholesale trade, retail trade, or accommodation, cafes and restaurants industries (F, G and H in ABS classification), and 0 if otherwise	.16 (obs. 2064)	.36
ind5	Takes 1 if in transport and storage, or communication services industries (I & J in ABS classification), and 0 if otherwise	.10 (obs. 2064)	.30
ind6	Takes 1 if in finance and insurance, or property and business services industries (K & L in ABS classification), and 0 if otherwise	.15 (obs. 2064)	.35
ind7	Takes 1 if in government administration and defence, education, or health and community services industries (M, N & O in ABS classification), and 0 if otherwise	.16 (obs. 2064)	.36
ind8	Takes 1 if in cultural and recreational services, or personal and other services industries (P & Q in ABS classification), and 0 if otherwise	.06 (obs. 2064)	.24
occmng	Takes 1 if being managers and administrators, and 0 if otherwise	.14 (obs. 2061)	.35
occprf	Takes 1 if being professionals, and 0 if otherwise	.20 (obs. 2064)	.40
occassprf	Takes 1 if being associate professionals, and 0 if otherwise	.14 (obs. 2064)	.34
occtrade	Takes 1 if being tradepersons and related workers, or advanced clerical and service workers, and 0 if otherwise	.19 (obs. 2064)	.39
occinterm	Takes 1 if being intermediate clerical, sales and service workers, or intermediate production and transport workers, and 0 if otherwise	.22 (obs. 2064)	.42
occelbr	Takes 1 if being elementary clerical, sales and service workers, or labourers and related workers, and 0 if otherwise	.10 (obs. 2064)	.31
unemp	Takes 1 if being unemployed but looking job, and 0 if otherwise (in bigger male sample)	.073 (obs. 4797)	.26
age	age (in bigger male sample)	38.66 (obs. 5788)	13.80

Note: obs. is a short for observation.

Table 2: Regression Results by OLS

Dependent variable: lhwage

Variables	**OLS1-1**	**OLS2-1**	**OLS 3-1**	**OLS 4-1**	**OLS 1-2**	**OLS 2-2**	**OLS 3-2**	**OLS 4-2**	**OLS 1-3**	**OLS 2-3**	**OLS 3-3**	**OLS 4-3**
schooling	.073**	.074**	.063**	.050**	-.143✓	-.160✓	-.092✓	-.033✓				
schooling2					.012✓	.0136✓	.008✓	.003✓				
schooling3					-.0002✓	-.00024✓	-.0001✓	.00003✓				
postgrad									.473**	.472**	.424**	.348**
bachelor									.393**	.405**	.340**	.267**
diploma									.228**	.226**	.183**	.125**
certific									.027	.026	.034	.013
exper	.014**	.014**	.015**	.015**	.016**	.016**	.017**	.016**	.018**	.018**	.018**	.017**
exper2	-.00024**	-.00023**	-.00025**	-.00026	-.0003**	-.0003**	-.0003**	-.0003	-.00035**	-.00035**	-.00035**	-.00033**
tenure	.0095**	.0057✓	.0056✓	.0034✓	.0090**	.0054✓	.0054✓	.0033✓	.009**	.0053✓	.0054✓	.0032✓
tenure2	-.00013	-.00005✓	-.00004✓	0✓	-.00012	-.00004✓	-.00004✓	0✓	-.0001	-.00003✓	-.00003✓	0✓
jstress												
jcomplx												
English		.080	.113	.092		.093	.123	.103		.132	.154	.129
health		.292**	.306**	.287**		.283**	.298**	.278**		.261*	.279**	.259**
union		.112**	.122**	.147**		.113**	.124**	.148**		.114**	.123**	.148**
riskp												
ind1-8			√ (✓)	√ (✓)			√ (✓)	√ (✓)			√ (✓)	√ (✓)
occmng-lbr				√ (✓)				√ (✓)				√ (✓)
Constant												
Adj-R^2	0.1457	0.1589	0.2123	0.2251	0.1513	0.1646	0.2156	0.2277	0.1521	0.1654	0.2130	0.2270

Notes: * Significant at 5% level; ** significant at 1% level; ✓ jointly significant at 5% level; √ other variables included in the model.
For a person with about 13 years of schooling (the sample average), the estimated marginal rates of return to education are respectively 6.76%, 7.2%, 6.53% and 6.02% in the non-linear schooling models 1-2, 2-2, 3-2 and 4-2.

Table 3: Results by IV Method

Dependent variable: lhwage
Instrument for schooling: pschooling

Variables	**IV1-1**	**IV 2-1**	**IV 3-1**	**IV 4-1**
schooling	.083**	.084**	.069**	.049*
schooling2				
schooling3				
postgrad				
bachelor				
diploma				
certific				
exper	.014**	.014**	.016**	.016**
exper2	-.0002*	-.0002*	-.0003**	-.0003**
tenure	.0076*✓	.0036	.0037 ✓	.0018
tenure2	-.0001✓	0	0 ✓	.00004
jstress				
jcomplx				
English		.074	.127	.114
health		.222	.245	.221
union		.116**	.126**	.147**
industry			√ (✓)	√ (✓)
occupation				√ (✓)
constant	√	√	√	√

Notes: * Significant at 5% level; ** significant at 1% level; ✓ jointly significant at 5% level;
√ other variables included in the model.

Table 4: Results by Proxy Method:

Dependent variable: lhwage
Jcomplx and jstress jointly as proxy of working ability

Variables	P1-1	P2-1	P3-1	P4-1	P1-2	P2-2	P3-2	P4-2	P1-3	P2-3	P3-3	P4-3
schooling	.066**	.067**	.058**	.047**	-.106➷	-.124➷	-.077➷	-.029➷				
schooling2					.009➷	.0111➷	.0068➷	.0021➷				
schooling3					-.0001➷	-.00019➷	-.00008➷	.00004➷				
postgrad									.423**	.424**	.390**	.333**
bachelor									.341**	.353**	.295**	.239**
diploma									.214**	.214**	.172**	.128**
certific									.020	.020	.024	.007
exper	.013**	.013**	.014**	.014**	.015**	.015**	.015**	.016**	.017**	.017**	.017**	.017**
exper2	-.0002**	-.0002*	-.0002*	-.0002**	-.0003**	-.0003**	-.0003**	-.0003**	-.0003**	-.0003**	-.0003**	-.0003**
tenure	.0078*➷	.004➷	.004 ➷	.003 ➷	.008* ➷	.004 ➷	.004 ➷	.003 ➷	.007* ➷	.004 ➷	.004 ➷	.003
tenure2	-.00005➷	-.00002➷	0 ➷	.00002 ➷	-.00005 ➷	-.00002 ➷	0 ➷	.00003➷	-.00004 ➷	.00003➷	.00001 ➷	.00003
jstress	-.020**	-.019**	-.016*	-.017*	-.020**	-.019**	-.016*	-.018*	-.020**	-.019**	-.016*	-.017*
jcomplx	.027**	.035**	.031**	.023**	.033**	.034**	.030**	-.022**	.034**	.034**	.031**	.022**
English		.236**	.246**	.217**		.245**	.254**	.226**		.264**	.271**	.243**
health		.278	.282	.263		.262	.267	.248		.232	.242	.223
union		.109**	.123**	.143**		.110**	.124**	.144**		.111**	.124**	.144**
industry			√ (➷)	√ (➷)			√ (➷)	√ (➷)			√ (➷)	√ (➷)
occupation				√ (➷)				√ (➷)				√ (➷)
constant	√	√	√	√	√	√	√	√	√	√	√	√
R^2	0.1580	0.1732	0.2264	.2374	0.1622	0.1773	0.2298	0.2406	0.1638	0.1786	0.2286	0.2409

Notes: * Significant at 5% level; ** significant at 1% level; ➷ jointly significant at 5% level; √ other variables included in the model.
For a person with about 13 years of schooling (the sample average), the estimated marginal rates of return to education are respectively 7.5%, 6.8%, 5.9%, and 4.6% in the non-linear schooling models 1-2, 2-2, 3-2 and 4-2.

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