The Decision of Work and Study and Employment Outcomes

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1. Introduction

Working-while-schooling has received a lot of attention from both educators and the general public. Some argue that working while attending schools will reduce time students spend on their school work and thus affect the quality of the education they receive. A counter argument is that students with more working experience during schooling will be better prepared for their transition to the future labour market.

Discussions of effects of working while in school on education and labour market achievements have been largely developed in the literature using US and European data. Nowadays, in many countries it is common for students to have some type of employment experience during their school time. According to Light (2001), for male students aged 16 and above, a cumulative average of approximately 200 hours are spent working in the US. Statistics show that, in Europe, fractions of student workers differ from country to country but with a uniform pattern that more than half of the students take a certain form of employment while enrolled in universities (Euro Student, 2000). Canada is not an exception in this regard. Using the General Social Survey (GSS), Franke (1998) shows that about 62 percent of boys and 69 percent of girls take some form of job during their high school studies. These numbers are higher for post-secondary students, 76 percent and 83 percent respectively.

There is a large body of literature studying the effects of working experience accumulated in high school, however, the effects of working experience obtained in universities are rarely investigated. It is a well known fact that employment is more common among university students and university students may have very different reasons to participate in the labour market activities. For example, they may work to pay

tuition fees, cover accommodation and transportation expenses if living away from parents, maintain certain life style and consumption habits and most importantly, they may be motivated by the fact that they can earn additional working experience to prepare themselves for their future career endeavours. It is very important to study the factors that may contribute to the decision of sharing between work and study of our university students in order to evaluate our current policy on post-secondary education. This is an important issue that this paper intends to address.

The debate over the appropriateness of tuition fee policy for post-secondary education has always drawn great attention from policy makers and the public. In Canada, university tuition fees have experienced dramatic increase since 1990. For example, the average undergraduate student faced a tuition fee of $1,464 in 1990/1991. Average tuition fees have almost tripled by the 2006/2007 academic year, when the average student paid $4,374. Finding employment or increasing total hours of working becomes necessary for many students, especially for those from lower socio-economic families. In addition, subject to their limited annual budget, some students may find it necessary to seek temporary employment in order to maintain the same consumption level when their education expenses increase. In other words, university students may find that it is necessary to seek employment while in school, though the motivations may differ by their family background. It would be interesting to investigate how family backgrounds and education policies jointly influence the work decisions of university students.

Two goals are pursued by this study. First, it aims to delineate factors that may influence university students' working decisions. The Survey of Labour and Income

Dynamics (SLID) (1993-2004) from Statistics Canada is used for this purpose. In order to test the robustness of the results obtained by using SLID, the Youth in Transition Survey (YITS) is used as well. The second purpose of this paper is to estimate the impact of working experience obtained in universities on individual's future labour market achievements, such as the probability of getting a job and the resulting wage level of those individuals.. For this second issue, only SLID data are used, as the sample size of those who graduated from universities for at least one year is too small in YITS.

The empirical results from this study show that increasing tuition fees tends to increase university students' total yearly working hours significantly. It is also observed, by using YITS, that the increase of tuition fees seems to make university students work more in the periods when they are not exposed to studying pressures, such as during the summer and other inter-semester break times. The working decision is also influenced by factors such as family financial support and the local unemployment rate. As for the labour market successes after graduation, linear regression results indicate a positive and significant effect of in-university working experience on both the future probabilities of getting a job and the resulting wage level. It also shows that the in-university working experience effect is stronger for the immediate period after graduation. Furthermore, the "treatment-effect" model and the Instrumental Variable (IV) estimation are also used to correct the selection bias that may be present in the data. The "treatment effect" model generates similar results as in the linear regression. However, IV estimates present a statistically insignificant effect of in-university working experience on later labour market achievements.

The rest of the paper is organized as follows: Section 2 summarizes previous literature related to this study. Section 3 describes the data and variables used in the quantitative analyses. Section 4 presents the methodologies adopted in the paper and the empirical results. Section 5 concludes the paper.

2. Literature review

There have been a number of studies on the determinants of labour market participation and working hours for youth. However, most of the studies have concentrated on high school students and focused on family background factors. Apparently, the relationship between tuition fees and labour market decisions has eluded investigation in the past. Earlier research includes Rees and Gray (1982), Goldfarb and Yezer (1983), Michael and Tuma (1984) and Schill, McCartin, and Meyer (1985). They all use US data to examine how family backgrounds influence the labour market participation for youth. Family backgrounds, such as family income, parental occupation, sibling characteristics, are shown to be influential factors, although there have been no uniform conclusions on each determinant's effect. For example, the sibling effect is significant in Rees and Gray (1982) but not strong in Goldfarb and Yezer (1983). Ransom (1996) found that youth from medium income level families work more than those from both lower and higher income families. O'Regan and Quigley (1998) addressed the influence of neighbourhood composition on employment probabilities. UK data were used by Dustmann, Micklewright and Rajah (1996), Dustmann, Rajah and Smith (1997), for which gender difference and parental income effects are the focus. In addition, the tuition fee is added as another important factor of interest in the investigation of working decisions of university students.

Similarly, there is no consensus on the influence of working-while-schooling on academic performance based on the literature available. Earlier work includes Paul (1982), Hood, Craig and Ferguson (1992), and Ehrenberg and Sherman (1987). Recently, Stinebrickner and Stinebrickner (2003) used data from one US college investigate this relationship as well. Ruhm (1997) made a thorough overview of the literature and pointed out that the differences in conclusions are due to differences in data and the methodologies adopted.

There is a rich literature on the economic returns to in-school work experience. Light (2001) tested the effect of working-in-school on post graduate wage by using a male subsample of the US National Longitudinal Survey of Youth (NLSY). His study shows that in-school working experience presents a positive relationship with after-school wages. Thus, the traditional return to education model is challenged as to whether the experience from school should be included. In other words, the traditional estimation of the coefficient in front of the education variable might be over-estimated, as it takes some role from the variable representing working while attending school when the latter is not included in the model. Hotz et al (1999) also examined the relationship between working in college and subsequent wage levels by using the male subsample from the NLSY. Hakkinen (2004) used Statistics Finland's Employment Statistics (ES) to study the influence of working while attending universities on post-graduate job accessibility and wage levels. In Hakkinen's (2004) study, linear regression estimates show that working experiences in university positively influences the wage level after graduation only for the first few years. IV estimation is adopted to correct for the selection bias, and

it shows no significant influence of student employment on their later labour market success.

Canadian literature on how in-university work experience influences the educational and occupational achievements is relatively limited. Parent (2006) uses Statistics Canada's 1991 School Leavers Survey (SLS) and its 1995 follow-up to examine the consequences brought by working-in-high-school. The results show that working while attending high school presents a strong negative effect on graduation rates for males and relatively ambiguous effect on females. In addition, working experience accumulated during high school study years does not contribute to future labour market achievement such as wage levels. Parent's (2006) study is based on a subsample of individuals who finished (or dropped) their high school without further education. Motivation for working while in universities might be different from high school and their consequences on labour market achievements deserve a separate study.

3. Data and variables

SLID and YITS are two longitudinal surveys conducted by Statistics Canada. SLID is a household-based survey combining information on labour market activities with income sources. Information on family backgrounds is available in SLID. YITS is conducted every two years to follow young people in their school-work transition period. YITS is composed of two cohorts. One cohort is for youth who were 15 years old when the survey was first conducted in the year 2000. The other cohort consists of a sample of 18-20 years old when YITS was conducted the first time. The second cohort (or cohort B) is used in this paper. YITS collects more detailed information related to education, such as student loans and family financial support. This provides a more accurate description

of students' financial situation. University names and the major field of studies are explicitly given in YITS. Thus, it provides a more reliable way to obtain information on tuition fees faced by each individual. Monthly working and studying status are also given, allowing the derivation of total working time vis-à-vis length of time registered as a student. SLID covers a longer period of time compared to YITS. Years currently available for SLID are from 1993 to 2004. Three cycles are available for YITS, covering every year from 1999 to 2003. Working and studying status are collected for every year by YITS, but family support and student loan information is only available for 1999, 2001 and 2003[2]. For this paper, only year 1999, 2001 and 2003 of YITS are used. For SLID, all 12 years from 1993 to 2004 are used.

3.1 SLID data

The unit of analysis is the individual enrolled in a university as a full-time student for each year of the SLID survey. Here only full-time students are under investigation due to the following two reasons[3]. First, motivations for working while studying for full-time students are different from part-time students. Second, the tuition fee, which is one of the factors of interest, is not easily assigned to a part-time student. In estimating working decision models, the annual total paid working hours from all jobs are used as the explained variable for Tobit models. To estimate the probability of labour force participation while in universities, a binary variable is generated to indicate if a student works (with positive working hours) or not (0 working hours) for each year while

[2] In Cycle 2, work and study status are collected for both year 2000 and 2001. Family financial support and student loans information are only asked for 2001. This is also the case for Cycle 3, which covers year 2002 and 2003.

[3] The variables explicitly describing the full-time and part-time university participating activities is available since 2002. However, there is another variable about full-time and part-time school attendance without distinguish the level of education. By combining this information with the university participating variable, the full-time and part-time university students can be separated.

attending university. As this variable is binary, the Probit regression model is used. The outcome is the probability that a student would work while attending university. The main explanatory variables are discussed below.

Previous studies show that parental income is an important determinant of a student's working decisions. It is observed, by using the SLID dataset, that a certain fraction of university students live by themselves while attending universities. This makes it difficult to collect information on parental income. This is because in the SLID dataset, personal information is collected based on the household each person resides in. New household and new economic family identifications are generated for each student represented in SLID once the student moves away from home to attend university. This prevents us from obtaining the parental income and other family background information. There are two possibilities to consider. One possibility is that they are "co-residents" of a household when the survey was conducted[4]. For this type of student, there is no information retrievable about their family background. The other possibility is that the student started as an individual belonging to an economic family and did not claim themselves as the family head at the beginning of the survey. For this group of youth, they have their original household, economic family and personal identifications. They moved away to go to university sometime later. By using the unique personal identification, it is possible to trace back the original economic family identification when they were still living with their parents, although SLID assigns them with different household and economic family identifications for those years when they lived away from the parental household. As a result, family backgrounds are traceable for current

[4] They do not have economic relations with other people living in the same household. One example is that he/she is a tenant of the household to attend the university in the same city.

years when a student is in university but lives away from home. For others who keep living within the same household with their parents, parental income is easily obtained. This is the advantage of using longitudinal data, which cannot be realized by using cross-sectional data.

There is no information on either student loans or financial support from family members in SLID. In this situation, the parental income variable is actually used as a crude indicator of potential family support, the parental social network, working habits of family members, the usual life styles and the chances of getting a student loan. It should be pointed out that the effect of family income on work decisions for university students may be ambiguous. On one hand, students from higher income families are more likely to have financial support from their parents, which will reduce the incentive for working for the purpose of covering higher tuition fees and daily expenses. On the other hand, the probability of having a student loan[5] is lower for students from higher income families. They may, as a result, work more in order to cope with tuition fees increases and to maintain their usual life styles. Family income may also indicate, to some extent, the parental social network and working habits, which could influence the working decisions of students. Using one variable to take all the above factors into consideration makes it difficult to disentangle the effects of various factors. This shortcoming will be overcome by comparing the results using the YITS dataset, where more detailed information related to financial support for education purpose is available.

Working decisions, as discussed above, are also affected by many other factors. Tuition fees are one of the most significant costs associated with attending university.

[5] Government student loans and assistance are income tested. Private student loans may nevertheless be available to students from high income families.

Canadian universities have experienced a dramatic increase in tuition fees since 1990's. The starting reference year of SLID data is 1993. Therefore, the sample period does not cover both lower and higher tuition fees periods. However, even between 1993 and 2004, tuition fees also increased significantly for all universities. In SLID data, the name of the university and the major field of study are not collected. In this study, for those who are attending university, the tuition fee variable is generated by using fees of the Arts program of the biggest university for the province where students resided. It mimics the general increasing trend of tuition fees students have to pay over this period.

Local labour market conditions influence students' working decisions significantly as found in much of the literature. It is natural to take this information into consideration in economic modelling. Local unemployment rates are adopted in this study to mimic the local macro economic situation that a student was facing each year when looking for a job. Unemployment rates for Census Metropolitan Area (CMA) are assigned if students were residing in a CMA region. Otherwise, the provincial unemployment rates are used.

Other information used for each student includes gender, age, if the student had a child or not, if the student lived away from parents, years of enrolment in the university and total number of jobs worked each year. The working decision for graduate students is different from undergraduate students. A dummy variable is generated with a value of one to denote that the student has had a university degree and 0 otherwise. Provincial and year dummy variables are used as well to capture other factors which cannot be exhaustively included in the model.

As discussed above, the second goal of this paper is to estimate the returns to working experience accumulated while attending university. The sample used for this

issue focuses on students who have received university degrees for at least one year and are no longer attending university. Self-employed and Not-in-the-labour-force university graduates are excluded. Two measurements of labour market achievements after graduation are adopted. One is to use the wage for the major job as the dependent variable to estimate the influence brought by working experience accumulated while attending university. The other measurement is the employment probability after graduation. Specifically, in this study, a binary variable is generated. It is given a value of 1 if a university graduate works for more than 1000 hours (approximate half a year) per year. Otherwise, a value of 0 is assigned. The above two measurements conform to other literature so as to make the result comparable to other research. The working hours accumulated while in university are included on the right hand side of the regressions. Other regressors include local unemployment rate, gender, age, marital status, child information, years of schooling, graduation years, parental education levels, year and provincial dummies. More details about these models will be discussed in the next section.

3.2 YITS data

YITS is a longitudinal survey designed to provide policy-relevant information about school-work transitions and factors influencing pathways among education, training and work. The first data collection – Cycle 1 of the survey – for the cohort aged 18 to 20 (or Cohort B), was conducted by Statistics Canada between January and April 2000 with the co-operation and support of Human Resources Development Canada. In 2002 and 2004, these youth were re-interviewed to follow their work-study behaviours during each period since the last interview. The sample size shrank significantly in Cycle 2 and Cycle 3.

Totally, there are 22,378 observations in Cycle 1, but only 18,779 and 14,817 in Cycle 2 and Cycle 3 respectively.

YITS collects information on monthly work status for each person. This set of information includes if each individual is employed or not for each month. The yearly total working hours for each job are calculated by multiplying total months worked by monthly paid working hours[6]. YITS collects information on up to 7 jobs that each person could have worked for each period. The total working hours for all jobs are calculated by summing up annual paid working hours from all paid jobs. This "total working hours of all jobs" variable is used as the dependent variable in the Tobit model. With the same logic as in SLID, a binary variable is generated to indicate if the student had positive working hours or not and is used as the regressand for the Probit model. For each month, a question of "full-time post-secondary institution attendance status" is asked. Combining this information with the institution type, i.e. university or college, the monthly full-time university participating status is derivable. Specifically, the whole year is divided into 3 semesters, i.e. Winter (January-April), Summer (May-August) and Fall (September-December). For each semester, if a student has registered for at least 3 months, he/she is included in the sample for analysis. Based on registration information above, the total paid working hours for the corresponding registered semesters can be calculated separately without taking non-study-period working hours into consideration. In addition to total annual working hours, the variable "working hours with respect to the study period" is also used as the dependent variable for regression purpose. It offers supplementary results and a closer look of working decisions for university students.

[6] YITS provides average monthly paid working hours for both the starting and the most recent periods. In this study, the average monthly paid hours for the most recent period is adopted as they are more close to the period when working hours are under investigation.

Most of the corresponding independent variables as used in SLID can be found in YITS but they may not entirely agree. Particularly, there is no specific information about family income in YITS. A question about "total income received from parents or other people without having to be repaid (loans excluded)" is asked, which can be used as a proxy for financial support from families for post-secondary studies. The question is also asked about the total cumulative student loans a student has borrowed to fund his/her post-secondary study. With control of years enrolled in the university, the student loan information can be used to evaluate effects of student loan levels on working decisions. By separating the family financial support from student loans, the ambiguous effect of simply using family income, as in SLID, can be resolved.

The influence from the increase in tuition fees can be more accurately estimated by using YITS. Both university names and the major field of studies are specified in the survey. By combining institution information with the derived registration period as discussed above, tuition fees can be assigned accurately to each university student[7].

As information about universities' campus codes is explicitly given in YITS, the local unemployment rate can be assigned according to the economic region each campus is located[8]. YITS provides up to 4 institutions' information for each student. In this study, only the most recent enrolled university is under examination. YITS also provides detailed information on the level of education for each student, thus the graduate students

[7] For universities, the academic year is not the same as a calendar year. By having correct information of semesters students are enrolled in the universities, the tuition fees can be assigned accurately.

[8] In SLID, the geographic information is collected by using the location of the last day that each person stays in the reference year. The economic region information is also given by SLID. If using economic region to assign local unemployment rate for SLID data, it still refers to the location where he/she was staying the last day of the reference year. This might not be the location of university they attended. Therefore a more general provincial level unemployment rate is used in SLID. For YITS, this concern can be resolved as it is based on the campus location where the students were attending university.

can be separated from undergraduate ones. A graduate student dummy variable is created and used in the analysis.

Other related information is also available in YITS. For example, whether a student has a child, whether a student has moved away from parents' place, whether a student is enrolled in a co-op program and gender are all given.[9] More detailed information about moving away from the parents' house for the purpose of post-secondary education is provided by YITS. A set of dummy variables are generated accordingly. Specifically, variable "move away 1" is given a value of 1 if the student moves within the same city and 0 otherwise. Variable "move away 2" is given a value of 1 if the student moves to another city and 0 otherwise. Here, those who live with parents are used as the omitted group to avoid the dummy variable trap.

For both SLID and YITS, family income, the family financial support, tuition fees and the wage are all deflated by the major city CPI (1992=100) to make them represent the real measurements.

3.3 Trends of working while attending universities and summary statistics

Table 1 presents the probability of working while attending universities by parental income[10] quintile using SLID. It is observed that students from lower income families are less likely to be involved in the labor market when studying in universities. Table 2 tabulates the average total annual working hours for student workers by family income quintile, again using SLID data. There is not a clear pattern in Table 2 as in Table 1. Relatively speaking, working hours for students from the lowest income quintile families

[9] Age is excluded from YITS regressions. This is due to the multicollinerity problem between age and year dummies when the cohort data is used. Here year dummies are used to capture both age and other unobservable time effects.
[10] Parental income is adjusted by the square root of the family size.

are less than those from other quintiles. However, this pattern is not always the case. This unclear relation has been discussed in the previous section. The family financial support and the student loan affect work decisions in the same directions, but oppositely associated with family income. It is not easy to tell, by simply looking at Table 2, which effect is stronger. A more detailed analysis is needed to determine the directions of these effects.

Table 3 shows the probability of working while attending universities by gender for each year with use of SLID data. It is obvious that female students are more likely to take a certain form of work during their university studies than male students. However, a quick check of the total working hours of student workers for both genders reveals a different story. Table 4 presents the average working hours for both male and female student workers. It seems that, in terms of working hours, male students tend to work more than female students. This pattern persists in Table 5 and Table 6 which are based on data from YITS.

Table 7 shows that the probability of participating in labor force during university studies is generally higher for students registered in co-op programs. This is not surprising since, by the nature of the program, there is generally more working information for co-op students than for other students. The overall annual working hours, however, are not noticeably higher among co-op student workers as indicated in Table 8.

4. Methodologies and Empirical Results

4.1 Econometric models

Working hours for university students are non-negative values. In real data, we can only observe either positive or zero hours for each student. In other words, working hours

present censored variable characteristics. The underlying preferred hours of working while attending universities can be either positive or negative by using the index functions:

$$y_i^* = x_i\beta + u_i \tag{1}$$

$$y_i = y_i^* \quad if \quad y_i^* > 0 \tag{2}$$
$$y_i = 0 \quad if \quad y_i^* \leq 0$$

where y_i^* is the latent variable measuring underlying preferred hours of working while attending universities. Students will only choose to work if y_i^* is greater than 0. Otherwise they choose not to work. y_i^* is not observable in the data when it is less than 0. What is observed is y_i, which denotes the total working hours reported by each individual. Econometric methods on the censored variable should be adopted in this study to take the censored property of the "working hours" variable into consideration. If we ignore the censored property and use models based on continuous variable directly, the estimation will be biased. Either a Tobit model or an alternative to ML method proposed by Heckman (1979) will take the censored property into consideration. In this study, the Tobit model is employed to estimate the working decisions of university students[11]. The coefficients provided by Tobit estimation are the unconditional marginal effect of independent variables. Each coefficient represents the change of the unobservable latent variable subject to the unit change of the corresponding independent variable. It can be expressed as

[11] Tobit estimation is generally more efficient than Heckman's procedure.

$$\frac{\partial E\left[y_i^* \middle| x_i\right]}{\partial x_i} = \beta_i \tag{3}$$

If the observable variable y_i is under interest, the marginal effect becomes

$$\frac{\partial E\left[y_i \middle| x_i\right]}{\partial x_i} = \beta_i \Phi\left[\frac{\beta' x}{\sigma}\right] \tag{4}$$

It is obtained simply by scaling the β_i by the predicted probability in the uncensored regression (Green, 2000). In the empirical results analysis, the conditional marginal effect in (4) is reported, as it is usually the total working hours that are observed and the center of interest.

A general model is that the probability of a limited observation might be independent of the regression model for the non-limited data. For example, in this study, it is observed that female influence the probability of participating the labor force and total working hours in an opposite direction. In addition to the Tobit model, a Probit model is fitted by using a binary variable of working status as the dependent variable. Specifically, variable PWORK is given 1 if a positive number of working hours is observed from a student and 0 otherwise. All other variables are the same as in the Tobit model. The Probit model is estimated as

$$\text{Prob}(\text{PWORK} = 1 \mid \text{X}) = F(\text{x}\beta) \tag{5}$$

Having both Tobit and Probit estimation will provide a more comprehensive understanding of working decisions for university students. It allows for different effects on having a job versus having different hours once employed.

Descriptive statistics for dependent and selected independent variables, which are used in regression models, are presented in Appendix Table A1 and Table A2. Empirical results are presented in the following part of this section.

4.2 Estimating the working decision for university students by SLID

Results for Tobit and Probit models based on SLID are listed in Table 9.

Tobit results show a strong tuition fee effect on total annual working hours. Coefficients in front of the "tuition fees" variable and its square show that the influence from tuition fee change is generally concave, suggesting that higher tuition fees will force students to work more but with a decreasing trend. Using a specific example, if tuition fees increase from 1000 dollars to 2000 dollars and other variables unchanged, it will lead to an increase of 126 total yearly working hours on average (evaluated at $1,000). In other words, an increase of $1000 in tuition fees will lead to students working about 10.5 hours more each month, which translates into about half an hour each day. It needs to be noted that this increasing trend presents a decreasing pattern if tuition fees keep climbing up due to the concave relation between tuition fees and the total working hours.

Coefficients in front of adjusted parental income and the square of adjusted parental income suggest a concave shape of the parental income effect. However, this relationship is not statistically significant. As discussed above, the parental income influences students' working decision with an ambiguous pattern. The weak relationship presented by the Tobit model calls for a more detailed information of family financial support and student loans, which are available by using the YITS dataset.

As compared with a single male student, a single female student will work about 68 hours less on average each year. As for students with children, a female will work 156

hours less ((144-233-67)) than a single male student. A male student with children is expected to work more than a single male student without children, but the difference is not statistically big enough. Generally speaking, working hours differ between male and female students. If the student becomes a parent, the mother will decrease her working hours largely.

Generally, if students don't live in the same house with their parents, expenditures related to rental and transportation will be higher. The Tobit result shows that generally students will work about 107 hours more annually if students live away from the residence of their parents.

Students with university degrees at hand show a higher probability to work as compared with those who are the first time enrolled in a university. Those with a university degree in most cases are graduate students, who are more likely to obtain a job such as a teaching or research assistant. Whether students have a university degree is only a rough indicator for the graduate level education by using SLID. Results show that, on average, students holding a university degree work 62 hours more each year.

The CMA (or provincial) level unemployment rate is used to evaluate the impact from local macro economic situations on students' working behaviours. The marginal effect of the unemployment rate is negative and statistically significant at 10% level of significance. The absolute value of the marginal effect of the local unemployment rate doesn't provide substantial. It is probably because student workers are more likely to be involved in a labor-intensive field which is not sensitive to the local unemployment rate as other industries. Students can also take more than one part-time jobs to make the total working hours relatively stable.

Number of jobs holding by university students is also related to working hours. A concave relation exists between number of jobs and working hours. Adding one more job will increase average working hours. But this trend decreases gradually.

Controlling for other variables (or characteristics), students from single parent families don't present different working decisions compared with those with both parents. Students from immigration families will work 30 hours less each year. The effect of the latter variable is statistically significant.

Years of education have limited influence on working hours, although coefficients with respect to it and its square are statistically significant. Coefficients in front of CMA and year dummy variables don't present big difference of working hours among most locations and years[12].

Probability of working while attending universities is also estimated by using a Probit model. The dependent variable is binary, with 1 denoting working positive hours and 0 otherwise. Independent variables in the Probit model are the same as in the Tobit model. The only difference is that the number of jobs and its square are dropped on the right hand side of the Probit model for the purpose of making results with economic meanings. Both coefficients and marginal effects from Probit estimation are listed in columns 4-6 of Table 9[13].

According to the Probit results, tuition fees continuously play an important role in determining the probability of working while attending universities. Keeping other variables the same, the probability of participating labor force tends to increase if tuition

[12] Coefficients in front of CMA cities and year dummies are not listed to save space.
[13] Marginal effects of continuous variables for the Probit model are evaluated at the mean values of continuous variables and set all dummy variables equal to 0. The marginal effect for dummy variables is then calculated by switching from 0 to 1 one by one.

fees increase. The probability increases, when tuition fees are higher, but with a decreasing trend. Probit and Tobit results on parental income conforms to observations in Table 1 and Table 2, where probability of participating labor force is lower for students from lower income families but not obviously less in terms of working hours. Coefficient in front of female becomes positive and significant at 1% level of significance rather than negative and significant, contrary to the Tobit result. Single females are 2% more likely to take a job while attending the university than a single male student. However, in terms of working hours, they work significantly less than single males. In other words, single female students are more likely to take moderate working hour jobs while single male students work longer if have a job. This result is consistent with what has been observed in Table 3- Table 6. Other variables such as living away from parents, having a university degree and the local unemployment rate, continuously play important roles in the determination of working decisions. Students from immigration families are 6% less likely to work as compared with those from local families. This is probably because immigration families put more emphasis on academic than working performance. Another reason is that parents of immigrant families don't have strong network to help their children fit in a position.

To summarize results by using SLID, generally university students take some form of job while attending universities. Tuition fees always present to be a strong influence in both working probabilities and working hours. Keeping other factors the same, higher tuition fees tend to make more students work and also make student workers work more than before. Parental income presents a positive effect on working probabilities but ambiguous with respect to the amount of hours worked. Other factors also play important

role in determining both probabilities and hours of working. Female students would more likely to work but with fewer hours than male students.

4.3 Estimating the working decision for university students by YITS

In analyzing students' working decisions by using SLID data, important variables, such as tuition fees, are assigned according to the province where each student was residing rather than taken directly from the survey due to the restriction of information available. In contrast, YITS provides more information related to the education experience for each person. Specifically, names of the universities and the major field of studies are given explicitly, which make the tuition fee assignment more accurate. Annual paid working hours for each job are calculated by multiplying the total months worked by average monthly working hours for each university student. The total annual paid working hours are the summation of working hours from all jobs in each year.

The Tobit regression result from YITS (See Table 10) presents a similar tuition fee impact as in SLID. Increase in tuition fees positively influences students' working hours. An increase of 1000 dollars in tuition fees, from 1000 dollars to 2000 dollars, will make students work about 105 hours more each year. The annual total working hours for students who moved away from parental places but still stay within the same city are not significantly different from those living together with parents. For others who moved out of their hometowns, 30 more working hours are added each year. The difference is stronger for students who moved to a different city. The total annual working hours of students who are enrolled in a co-op program are less than the others on average. Single females work less than single males, which is consistent with the SLID result and Table

5. Male students with child (children) don't work significantly more than the benchmark category, i.e. single males, which is also the case by using the SLID dataset.

Family income effect is not tested directly in the analysis with use of YITS. In stead, variables representing family financial support, scholarship and student loans are used. All such information is directly available from YITS, which provides a more accurate approximation for incentives of working while attending universities. All above three factors are negatively correlated with the working hours. Specifically, *ceteris paribus*, having 10,000 dollars more family support will reduce annual working time by about 40 hours on average. A difference of 1,000 dollars in scholarship or bursaries is associated with a difference of 23 hours in annual working time. Having 10,000 dollars more in student loans accumulation generally increases the average working time of a student by 21 hours or so.

Recall the results of family income effect in using SLID, where an unclear family income influence is obtained. Since family financial support and student loan factors are separated and present significant impacts on the working hours, other aspects of family income effect, such as maintaining certain life styles, seem to be dominated by financial issue.

The effect of the local unemployment rate is negative but statistically insignificant. The local unemployment rate used in this analysis is based on the location of the university which each student attends. When the annual total working hours are under consideration, it is not difficult to understand this weak relationship. Hours of working from non-registration semesters are included for most university students, such as summer jobs. These students can move back and forth in the summer time to other

locations, depending upon where the labor market situation is ideal. Therefore, their total working hours might not be influenced largely by the local unemployment rate linked to the university location.

Compared with students in medicine program (the omitted group), there is almost no difference of working hours between programmes when other variables are under control. Coefficients in front of year dummy are significant from the base year 1999. Location differences, compared with non-CMA regions, are not strong.[14]

The Probit regression for YITS is also under investigation. According to the result, tuition fees play an important role in determining the working decision of a university student. The same as we have found by using SLID data, females are more likely to be involved in a work when attending the universities, but with a relatively smaller amount of working hours. The coefficient in front of the FEMALE variable in Probit model is also positive and statistical significant. Generally speaking, by using both SLID and YITS, female students would more like to take a certain form of work but only work moderate hours.

Family financial support, scholarships and student loan effects continue to have a strong and negative correlation with the probability of working for university students.

In the analysis of influence of tuition fee increase on students' working hours, province-based and programme-based tuition fees are assigned to each student for SLID and YITS datasets respectively. It could be the case that results obtained actually pick up the province labor market and programme effects by using this type of definitions respectively for the two datasets, although province and programme dummy variables are included in both models. To solve this concern, the first-difference of all changeable

[14] Results of these sets of dummy variables are not listed to make table short.

variables is calculated for each student if at least two years observations are available. An OLS regression is done with use of the first-order differentiated dataset. It shows that the coefficient in front of the change of tuition fees has a positive and significant impact on the change of total working hours for both SLID and YITS. These results, from a different angle, indicate that Tobit and Probit estimation reasonably evaluates the relationship between tuition fees and the working decisions for university students.

It also needs to be noted that the wage level is not considered in the current study. Wage levels may influence working decisions as well. e.g. a person could choose not to work as many hours as others if he/she works with a higher paid job. This may also be the issue for university students. SLID only provides wage information for the major job. Therefore it is not possible to deal with the case when students possess more than one job at the same time. By using YITS, the average wage by occupations is calculated for student workers (See Figure 1). It shows that about 50% of the student workers work in the service related field. The wage difference among occupations is not big for student workers. It is noticed that students working in applied science seem to earn more than other occupations. By controlling the programme of each student, this difference should be able to be caught.

4.4 Estimating the working decision for university students by YITS –study period only

YITS provides detailed information on all jobs taken in the reference year. It allows for up to 7 jobs at the same time. The monthly work status for each job is also available. Combining the monthly university participation status and work status for each student, it is possible to obtain the total working hours only for periods when the individuals registered and studied in universities. Thus, jobs not related to the study period, such as

summer jobs, are excluded from the model[15]. Tobit and Probit regression results with respect to working decisions only for the study period are presented in Table 11.

By only taking into consideration the number of hours worked while registering in universities, tuition fees do not present a significant influence on working hours. It shows that the increase of tuition fees will slightly reduce the working hours without significant change. e.g. for an increase of 1000 dollars in tuition fees (from 1000 to 2000 dollars as discussed above) only 11 working hours' reduce is observed on average for the whole study period. The corresponding influence of tuition fee increase on probabilities of labor force participation is also not statistically significant. As we observe the positive relationship between tuition fees and annual total working hours in previous subsections, it implies that higher tuition fees will more likely push students work harder in other time when no studies are involved, such as the summer period. They work harder to make up the expected increasing cost.

The local unemployment rate has a negative and significant effect on working hours and probabilities in this case. It is because when studying at universities, students are more restricted by the local labor market situation, as they generally cannot move far from the cities where the universities are located. While for non-registration periods, they can move back to where they used to live and to some other places with more working opportunities.

During the studying period, paid working hours for students enrolled in a co-op program are significantly higher than for those who don't belong to a co-op program. Important financial support factors, such as the family support, scholarships and

[15] SLID also provides monthly information about work and study status. For the work status, it is only with respect to the main job. For the study status, it doesn't indicate the level of education. Thus, in investigating the working behaviours when registering in universities, I just use YITS data.

accumulated student loans present negative significant influences on working hours and the probability of working during studies.

When students are studying in cities other than where they used to live, they both are less likely to work and, when they do, work fewer hours. This may because of the relative less network they possessed to access to work in the cities of universities. They make up this income loss during other period according to the result in Table 10. For those who only move within the same city to attend universities, no difference exists in both working hours and the probability of working during the period of studying.

Results obtained by using YITS, from Sections 4.3 and 4.4, can be summarized as follows. Generally speaking, tuition fees positively affect the total annual paid working hours for university students as well as the probability of labor force participation. Family background factors are important in determining the working decision as well. Students with more family support, more scholarships and more accumulated student loans are less likely to work. By looking into other details of this working decision issue, it seems that students would not change their working behaviour in their study periods much when exposed to a tuition fee increase. However, they work more in other time to make up the increased cost brought by higher tuition fees.

4.5 Estimating the returns to working experience in-university

After looking at the determinants of working decisions of university students, a natural question is raised that how this working experience contributes to their later labor market achievements, such as chances of finding a permanent job and the wage level. If working experience obtained while in universities positively influences the labor maket success, programmes that help student get involved in labor force should be encouraged.

If working hours accumulated while attending universities have only limited or even negative impact, higher tuition fees then simply increase students' working hours without additional human capital accumulation. As a result, the fast pace of tuition fees increase should be paid attention to by policy makers.

Most literature on the return to working hours accumulated while in universities has largely focused on high school working experience. In this study, the same question is addressed but for the working experiences cumulated while enrolled in a university. By using the SLID dataset, those who graduated from universities for at least one year and not in any form of post-secondary institutions are selected[16]. Based on the unique personnel identification, we can trace back years when they were still university students and find out the working experience information accordingly. Each wave of the SLID data covers at most 6 years, thus for some university graduates, no information for all university study years is available. In this paper, the average working hours of the last two years of university studies are used for the measurement of working experience accumulated in universities. Local unemployment rates for the last two years' of undergraduate studies are also averaged accordingly. Future labor market achievements are evaluated by two measurements: one for the probability of finding a job after graduation and the other for the wage level.

Finding a job after graduation is defined as being with paid working hours of at least 6 months each year. It is a commonly used measurement in the literature. With use of total annual paid working hours from SLID, if a person working for more than 1000 hours per year, he/she is defined to have found a job. Job search result dummy variable is

[16] The average age of individuals in cohort B from the most recently available dataset of YITS (Cycle 3) is between 22 to 24. Most of the university students just graduated. The one-year-after labor market behaviours are not observable yet.

only generated for those who have obtained their university degree for at least one year and not enrolled in a university anymore. Self-employed people and those who claimed themselves not in the labor force are excluded from the analysis. The following model is used to evaluate the return to experience accumulated in universities.

$$Findjob_i = x_i\beta + \gamma hours + u_i \tag{6}$$

Independent variables include average paid working hours for the last two years of university studies, current local unemployment rate, parental education, demographic characteristics (female, with kids and etc), years of schooling (and its square), years of after graduation (and its square), province dummies, and year dummies.

Only looking at the employment probability after graduation won't provide a comprehensive understanding of how working hours in-university contributes to the future labor market success. A more commonly adopted way is to estimate the wage equation by taking into consideration of the working hours accumulated. The wage equation is as follows.

$$\ln(wage_i) = x_i\beta + \gamma hours + u_i \tag{7}$$

OLS results show that working hours accumulated while attending universities have a positive and significant influence on the probability of getting a job. Coefficient in front of the variable HOURS (0.0000761) indicate that with 1000 more hours of working experience on average in the last two years of university education will increase the probability of finding a job by about 7.6%. Three additional regressions are estimated by only looking into each particular year after graduation. Years of graduation are excluded from these three models in this estimating process. It shows that in-university experience significantly influences the probability of finding a job in the first year after graduation

more than later. The subsequent three regressions related to each year after graduation suggest that this marginal effect changes from 10.9% for the first year to 7.1% and 6.0% for the second and the third year after graduation respectively. For the third year, the marginal effect becomes insignificant from 0. Briefly, working experiences accumulated while attending universities only influences the beginning period of labor market achievements.

OLS results on the semi-log wage model tell a similar story. The overall regression presents a positive and significant effect of working hours on wage levels. Coefficient in front of the hours accumulated in universities shows that the growth rate in wage level will be about 6.9% if 1000 more working hours are cumulated. For regressions focusing on each year after graduation, this growth rate is significant for the first two years with values of 7.9% and 7.8% respectively. The effect of accumulated working hours on wage diminishes and becomes less influential afterwards.

The OLS results simply report the return to working experience without correcting the selection bias. According to the analysis of previous subsections, the decision of hours of working is not a random process for university students. Students with higher unobserved abilities could work more during the school period. They would also benefit from these abilities in their future career attainment. In addition, the local macro-economic situation also influences the degree of labor force participation for university students. In this study, two techniques are applied to correct the endogeneity problem brought by the selection process. First, IV estimates are reported. This is the most commonly adopted methodologies in correcting selection bias when estimating the return to work experience in-school. Specifically, the local average unemployment rate of the

last two years' university studies is used as the instrumental variable. The choice of an appropriate instrument requires the instrumental variable to be correlated with the endogenous variable (working hours in-university here) but orthogonal to the residual term. Based on the Tobit and the Probit results in above subsections, the local unemployment rate significantly influence the students' working decisions and it is not correlated to personal abilities. The local labor market measurement has also been used by most literature as an instrument variable, such as Ruhm (1997), Light (2001) and Hakkinen (2006).

The local unemployment rate shows to be a good instrument by checking the first stage of all IV regressions. IV results generally don't present any significant effect of working experience in-university either on the job accessibility or on the wage growth. By correcting the selection bias, the positive and significant effect shown in OLS disappears.

The second method employed to deal with the endogeneity is to use the "treatment-effect" model as adopted by Ruhm (1997). For this method, a Probit model is first estimated with the dependent variable equal to 1 (0) if the student had positive (zero) working hours in the last two years of university studies. The Inverse Mills Ratio (IMR) derived from the Probit model is then added as an additional covariate for the second stage estimation of the employment probability and wage equations[17][18].

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[17] If the student had a positive (zero) working hours, the mill's ratio $\frac{\phi}{\Phi}(-\frac{\phi}{(1-\Phi)})$ is used. ϕ is the density function and Φ is the distribution function of standard normal. ϕ and Φ are evaluated at the inner product of probit coefficients and the individual attributes.

[18] The full model of first stage probit estimation for the "treatment effect" model is identical to equation (2) without taking family income into consideration, since family income effect is not significant as found in estimation results in section 4.2. The sample that ensures all individuals have valid past information is smaller. This is because that the last period parental income information is not available for part of the

The "treatment effect" result doesn't change the OLS pattern very much. This is due to the insignificance of the coefficient in front of the "Inverse Mill's Ratio (IMR)" term. It is because a large proportion of the university students work while schooling, which makes the variation of the first stage probability prediction and thus the variation of IMR small. The "treatment-effect" model doesn't resolve the selection bias successfully in this case.

Combining results from this section with the previous section, it shows that university students increase their working hours partly due to the higher tuition fees. These increased working hours mostly focus on jobs working in the periods when they are not registering in the universities. However, working experience accumulated doesn't contribute to their future labor market success largely, by using the IV results. Although, OLS shows a significant positive influence of the working experience on after-graduation labor market achievements, this effect diminishes fast and become insignificant 3 years after graduation. The high tuition fee policy tends to make university students work more than before to make up the higher cost, but the increased working experience doesn't help accumulated human capital dramatically.

It should be noted that, to estimate the wage equation, only those who report the valid values of wages are used. The selection issue on the right hand side of the equation (work-or-not-in-university) is taken into consideration. The sample selection issue, i.e. we only observe wages when people are working, is not taken into consideration in

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sample for OLS regression. To check if results will change, the OLS regression with use of the subsample is re-estimated to see if the coefficients are sensitive to this change. It shows that the trend doesn't change due to the use of subsample. Both IV and "treatment effect" methods are applied on the subsample to correct the selection bias existed in the OLS results. Particularly, when estimating the "treatment-effect" model, the family income is added to the first stage Probit model. There is no significant change as compared with the case when the full sample is used without including family income in the Probit model for the "treatment-effect" model. IV also persists the same pattern as by using the full sample.

current study. In other words, a double selection issue exists in the wage equation (7). One is for the dependent variable and the other one is for the independent variable. The above methods are the typical ways adopted by the most literature, where only observations with valid wage are used and the concerns are paid to the selection bias introduced by the "working hours" variable. There is actually a very tiny amount of observations without reporting valid wage levels, disregarding the total hours they worked. This small proportion of observations won't be a big issue for this study.

5. Conclusion

Two issues are addressed in this paper by using Survey of Labor and Income Dynamics (SLID) (1993-2004) and Youth in Transition Survey (YITS) (1999-2003) from Statistics Canada.

The first part of the paper tries to model the working decisions of university students. Factors such as tuition fees and family backgrounds are shown to be important determinants in both working hours and probabilities. Using detailed information about working and studying status in YITS, it is found that higher tuition fees influence the total annual working hours positively but not for working decisions related to the period when students are studying at universities. Family financial support and student loan effect are also important forces. Female students seem more likely to work moderate hours but with a higher probability of participating labor force compared with males. Local unemployment rates affect the working behaviours as well.

The second part of the paper tries to evaluate the return to working experience cumulated while attending universities. OLS results show positive and significant effect on both probability of getting a job and wage levels after graduation. By looking at each

year after graduation, the strong effect occurs for those years close to graduation. This positive effect diminishes and becomes insignificant quickly. IV regressions are estimated to correct the selection bias. IV results don't show significant influence of working experiences obtained while attending universities on students' future labor market success.

The two parts of the study evaluate the influence of higher tuition fees on university students' working decision intensively and extensively. Analysis results present that university students works more partly due to the higher tuition fees they are facing. This is particularly true for those who cannot obtain much financial support from families. However, the additional working hours limitedly influence their future labor market attainments. Higher tuition fees may also force students to bear more debt in exchange for their university education. This may affect their future net worth after graduation and their decisions on the choice of jobs. Instead of taking time and planning their career, some students may be obliged to accept work suboptimally as opportunities arise, which may also affect their long-run return to education. As short-run actions may have long-run consequences, if tuition fees are a factor that influences a student's choice between work and study, it may eventually affect long-run potential as well.

Figure 1: Student Job by Occupation

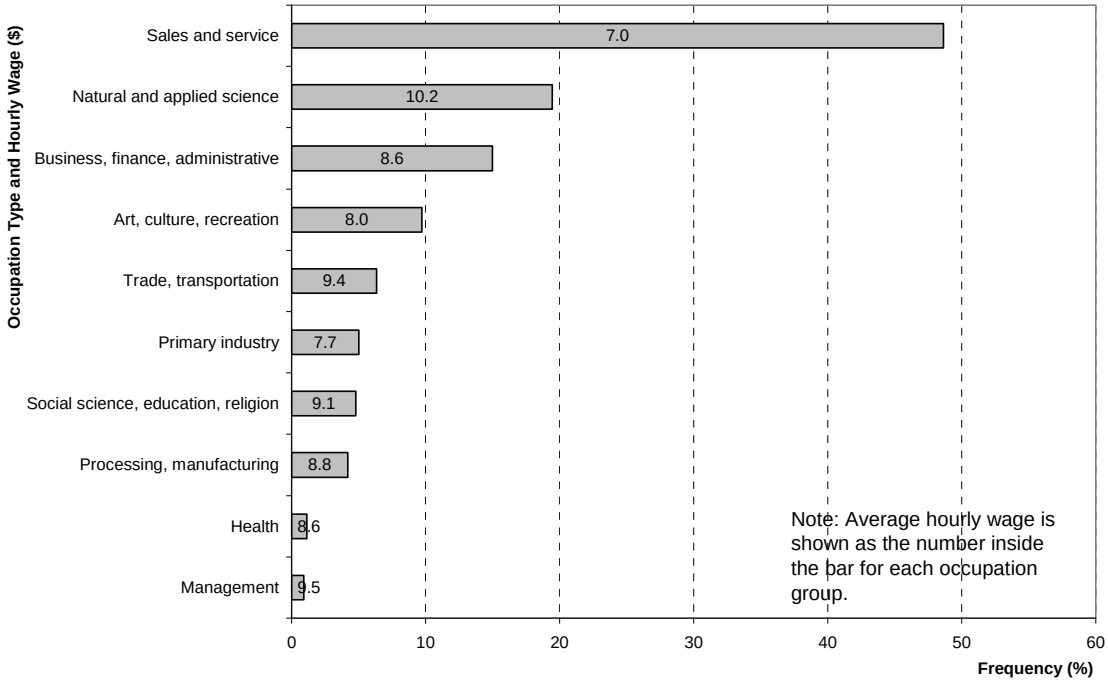

Table 1: Probability of Labor Force Participation by Income Quintiles (SLID)

Year	*Quintile of Income*				
	1	2	3	4	5
1994	0.83	0.92	0.75	0.81	0.90
1995	0.65	0.81	0.88	0.74	0.76
1996	0.63	0.83	0.82	0.82	0.73
1997	0.65	0.74	0.79	0.80	0.83
1998	0.59	0.71	0.83	0.85	0.77
1999	0.65	0.81	0.72	0.79	0.81
2000	0.67	0.68	0.77	0.79	0.70
2001	0.63	0.72	0.82	0.87	0.86
2002	0.77	0.82	0.89	0.83	0.83
2003	0.78	0.76	0.82	0.87	0.80
2004	0.70	0.77	0.86	0.86	0.81

Table 2: Average Working Hours by Income Quintiles (SLID)

Year	*Quintile of Income*				
	1	2	3	4	5
1994	601	798	718	808	889
1995	685	830	695	820	699
1996	812	861	771	583	720
1997	709	797	682	772	851
1998	874	907	764	780	875
1999	702	778	732	847	827
2000	730	851	778	885	941
2001	835	782	742	879	883
2002	680	821	728	810	1000
2003	843	844	950	880	871
2004	840	995	841	842	789

Table 3: Probability of Labor Force Participation by Genders (SLID)

Year	*Male*	*Female*
1993	0.86	0.88
1994	0.82	0.86
1995	0.76	0.79
1996	0.66	0.72
1997	0.77	0.76
1998	0.69	0.80
1999	0.67	0.79
2000	0.73	0.72
2001	0.73	0.81
2002	0.67	0.80
2003	0.78	0.83
2004	0.79	0.82

Table 4: Average Working Hours by Genders (SLID)

Year	*Male*	*Female*
1993	782	625
1994	772	762
1995	823	691
1996	762	746
1997	778	758
1998	895	800
1999	772	764
2000	844	838
2001	888	796
2002	843	820
2003	950	853
2004	935	834

Table 5: Probability of Labor Force Participation by Genders (YITS)

Year	*Male*	*Female*
1999	0.54	0.58
2001	0.83	0.85
2003	0.85	0.91

Table 6: Average Working Hours by Genders (YITS)

Year	*Male*	*Female*
1999	997	889
2001	1016	937
2003	1003	956

Table 7: Probability of Labor Force Participation by if in Co-op Program (YITS)

Year	*In Program*	*Not in Program*
1999	0.77	0.55
2001	0.89	0.83
2003	0.90	0.88

Table 8: Average Working Hours by if in Co-op Program (YITS)

Year	*In Program*	*Not in Program*
1999	1089	924
2001	994	965
2003	955	988

Table 9: Working Decisions of University Students (SLID) (1993-2004)

Dependent Variable	Tobit			Probit		
	Total Paid Working Hours			If participate Lbaor Force		
	Coef.	Std.	Marginal Effect	Coef.	Std.	Marginal Effect
Tuition	0.2279	0.0880	0.1734	0.0012	0.0002	0.0002
Tuition2	-3.14E-05	0.0000	0.0000	-2.03E-07	4.10E-08	-3.89E-08
Parental Income	0.0007	0.0006	0.0005	5.71E-06	1.52E-06	1.09E-06
Parental Income2	-1.46E-09	0.0000	0.0000	-1.34E-11	8.54E-12	-2.56E-12
Female	-88.7566	12.9517	-67.5438	0.0979	0.0354	0.0177
Female*Children	-306.3869	152.0035	-233.1604	-0.1484	0.3581	-0.0310
Children	189.8409	133.6253	144.4689	-0.4771	0.3200	-0.1185
Live away	141.2070	17.6200	107.4585	0.1916	0.0526	0.0326
With a University Degree	80.8646	20.1076	61.5379	0.2227	0.0561	0.0371
Unemployment Rate	-4.4181	2.3298	-3.3622	-0.0237	0.0063	-0.0045
Education Year	-15.4318	5.9336	-11.7436	-0.0409	0.0152	-0.0078
Education Year2	0.1507	0.0579	0.1147	0.0004	0.0001	0.0001
Age	190.3554	42.5275	144.8605	0.3397	0.1101	0.0651
Age2	-3.3600	0.9383	-2.5569	-0.0080	0.0024	-0.0015
Number of Jobs	1228.3010	22.3872	934.7371		--	
Number of Jobs2	-230.6789	6.0549	-175.5466		--	
Single Parent Family	-12.4809	17.8322	-9.4980	0.0036		0.0007
Immigrant Family	-39.2137	16.4741	-29.8416	-0.2867		-0.0647
CMA Dummies		Yes			Yes	
Year Dummies		Yes			Yes	
Constant	-3148.0130	501.5946		-3.9360	1.3095	
Proportion Of working Positive Hours		0.7610				
Likelihood		-51258.17			-3398.821	

Table 10: Working Decisions of University Students (YITS) (1999-2003) (1)

Dependent Variable	Tobit			Probit		
	Total Paid Working Hours			If participate Lbaor Force		
	Coef.	Std.	Marginal Effect	Coef.	Std.	Marginal Effect
Tuition	0.1742	0.0254	0.1263	0.0004	5.16E-05	0.0001
Tuition2	-1.5E-05	2.01E-06	0.0000	-2.75E-08	3.81E-09	-8.77E-09
Unemployment Rate	-2.0739	4.2282	-1.5036	0.0169	0.0095	0.0054
Live Away1	0.2178	59.7156	0.1579	-0.0550	0.1273	-0.0178
Live Away2	42.0150	19.9096	30.4608	-0.0724	0.0431	-0.0236
Co-op	-82.8842	23.7571	-60.0911	-0.2537	0.0586	-0.0871
Education Year	745.7548	38.5703	540.6722	1.6563	0.0816	0.5276
Education Year2	-106.7426	6.6738	-77.3884			
Number of Jobs	841.4031	24.9883	610.0172		No	
Number of Jobs 2	-123.9695	5.3752	-89.8779		No	
Children	48.3919	162.2685	35.0841	-0.373	0.335	-0.1319
Female	-84.1838	17.5585	-61.0333	0.100	0.040	0.030667
Female*Children	-165.1265	209.6840	-119.7167	-0.211	0.408	-0.0716
Number of semesters attended in Ref. Year	440.4256	27.9947	319.3086	0.857	0.061	0.273067
Family Financial Support	-0.0055	0.0025	-0.0040	-1.4E-05	5.69E-06	-4.53E-06
Scholarships	-0.0320	0.0061	-0.0232	-5.6E-05	1.24E-05	-1.8E-05
Cumulated Student Loans	-0.0029	0.0012	-0.0021	-8.78E-06	2.75E-06	-2.80E-06
Major Field of Studies Dummies		Yes			Yes	
CMA Dummies		Yes			Yes	
Year Dummies		Yes			Yes	
Constant	-2327	77.2618		-4.002	0.1541	
Proportion Of working Positive Hours		0.7250				
Likelihood		-49120.9			-2730.73	

Table 10: Working Decisions of University Students (YITS) (1999-2003) (2)

Dependent Variable	Tobit			Probit		
	Total Paid Working Hours			If participate Lbaor Force		
	Coef.	Std.	Marginal Effect	Coef.	Std.	Marginal Effect
Tuition	-0.012	0.016	-0.0082	4.77E-05	4.56E-05	1.44E-05
Tuition2	4.65E-07	1.29E-06	3.17E-07	-4.94E-09	3.53E-09	-1.49E-09
Unemployment Rate	-7.5165	2.7510	-5.1270	-0.0251	0.0076	-0.0076
Live Away1	-16.2682	37.8760	-11.0965	-0.1866	0.1084	-0.0600
Live Away2	-86.5025	12.9829	-59.0033	-0.6149	0.0357	-0.2197
Co-op	33.8014	14.9736	23.0560	-0.0381	0.0440	-0.0117
Education Year	-114.5792	25.2565	-78.1545	0.1573	0.0725	0.0474
Education Year2	15.7935	4.4103	10.7728			
Number of Jobs	913.5505	19.7026	623.1328		No	
Number of Jobs 2	-160.0448	4.5862	-109.1666		No	
Children	15.8143	109.2086	10.7869	-0.2843	0.2901	-0.0941
Female	-38.7479	11.5216	-26.4299	0.1484	0.0327	0.0422
Female*Children	-94.1768	140.8779	-64.2380	-0.2412	0.3630	-0.0789
Number of semesters attended in Ref. Year	380.4036	18.4048	259.4733	0.3472	0.0527	0.1046
Family Financial Support	-0.0063	0.0015	-0.0043	-1.7E-05	3.67E-06	-4.97E-06
Scholarships	-0.0218	0.0040	-0.0149	-5.1E-05	9.96E-06	-1.5E-05
Cumulated Student Loans	-0.0009	0.0005	-0.0006	-2.26E-06	1.17E-06	-6.82E-07
Major Field of Studies Dummies		Yes			Yes	
CMA Dummies		Yes			Yes	
Year Dummies		Yes			Yes	
Constant	-834.9433					
Proportion Of working Positive Hours		0.6821				
Likelihood		-47142.4			-4404.9	

Table 12:
Impact of Working Hours in the Last Two Years of Universities on Job Search Result

	OLS	IV	Treatment-Effect
Overall	0.0000761	-0.0000173	0.0000686
(n=1632)	(0.0000151)	(0.0000132)	(0.0000159)
		-38.95086	0.1076753
First-stage/IMR		(8.370306)	(0.0931262)
First year after graduation	0.0001087	0.0000353	0.000108
(n=626)	(0.000027)	(0.0002485)	(0.000027)
		-51.09343	0.2895563
First-stage/IMR		(19.1475)	(0.2152102)
Second year after graduation	0.0000713	-0.0000359	0.0000584
(n=459)	(0.0000275)	(0.0002131)	(0.0000271)
		-56.14694	0.2984979
First-stage/IMR		(20.61159)	(0.1558916)
Third year after graduation	0.0000603	-0.0000109	0.0000614
(n=309)	(0.0000381)	(0.0003058)	(0.0000384)
		-35.84541	0.0370644
First-stage/IMR		(0.037)	(0.1732353)

Table 13:
Impact of Working Hours in the Last Two Years of Universities on Wage Level

	OLS	IV	Treatment-Effect
Overall	0.0000689	-0.000084	0.0000707
(n=1621)	(0.0000181)	(0.0001577)	(0.0000195)
		-39.19862	-0.2012408
First-stage/IMR		(8.329058)	(0.1137017)
First year after graduation	0.000079	-0.0001893	0.0000914
(n=621)	(0.000031)	(0.0002906)	(0.0000324)
		-52.4478	0.1412355
First-stage/IMR		(19.04260)	(0.2499753)
Second year after graduation	0.0000776	0.0000367	0.0000802
(n=456)	(0.0000346)	(0.0002563)	(0.0000367)
		-57.00638	-0.189076
First-stage/IMR		(20.36981)	(0.2043109)
Third year after graduation	0.0000364	-0.0000687	0.0000334
(n=307)	(0.000041)	(0.0003395)	(0.000042)
		-34.69919	-0.1891394
First-stage/IMR		(17.06764)	(0.1888908)

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Appendix

Table A1: Basic Statistics of SLID data

(Sample used for estimating the working decisions)

Variable	*Number of Observations*	*Mean*
Total Working Hours	7919	701.099
If Participating Labor Force	7919	0.833
Tuition	7919	2709.267
Parental Income	7919	27777.040
Female	7919	0.590
Female*Children	7919	0.008
Children	7919	0.011
Live away	7919	0.163
Degree	7919	0.183
Unemployment Rate	7919	8.854
age	7919	21.580
Education Year	7919	5.152
Single Parent Family	7919	0.173
Immigrant Family	7919	0.239

Table A2: Basic Statistics of YITS data

(Sample used for estimating the working decisions)

Variable	*Number of Observations*	*Mean(1)*	*Mean(2)*
Total Working Hours	8345	717.581	408.169
If Participating Labor Force	8345	0.745	0.740
Tuition	8345	3071.809	3071.809
Unemployment Rate	8345	7.044	7.044
Live away1	8345	0.021	0.021
Live away2	8345	0.307	0.307
Number of jobs	8345	1.394	1.309
Co-op	8345	0.183	0.183
Education years	8345	2.479	2.479
Children	8345	0.006	0.006
Female	8345	0.562	0.562
Female*children	8345	0.004	0.004
Total semester in Ref. Year	8345	1.880	1.880
Family Financial Support	8345	2359.670	2359.670
Scholarship	8345	679.454	679.454
Cumulated Student Loans	8345	3689.060	3689.060