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Résumé / *Abstract*

L'objectif poursuivi dans cet article est d'évaluer l'effet du travail durant les douze mois précédant la date de sortie des études secondaires, soit comme diplômé soit comme décrocheur, sur la probabilité d'obtenir le diplôme. À cette fin, j'utilise les données de l'Enquête sur les sortants effectuée en 1991 ainsi que celles du Suivi de 1995. Étant donné l'endogénéité des deux variables d'intérêt, la diplômation et le travail pendant les études, j'utilise les conditions du marché du travail local comme instrument afin d'étudier la sensibilité des résultats par rapport à plusieurs techniques d'estimation dans le cadre d'un système de variables dépendantes qualitatives/limitées. Bien que toutes les méthodes d'estimation mènent plus ou moins à la même conclusion du point de vue qualitatif, l'utilisation de méthodes semi-paramétriques tend à accentuer l'impact estimé du travail sur la probabilité d'abandon par rapport aux techniques faisant appel au maximum de vraisemblance. En conclusion, contrairement aux résultats avec des données américaines qui tendent à être quelque peu ambigus, les résultats obtenus ici avec des données canadiennes sont non-équivoques : le travail pendant les études réduit substantiellement la probabilité d'obtenir le diplôme d'études secondaires. Cette constatation s'applique aussi bien lorsque j'utilise les heures travaillées que lorsque j'utilise une variable dichotomique pour le travail.

The objective of this paper is to assess the impact of working in the twelve months preceding the date of leaving high school, either as a graduate or as a dropout, on the probability of graduation. To do so, I use Statistics Canada's 1991 School Leavers Survey and its 1995 Follow-up. Given that both the decision to graduate and the decision to work are endogenous variables, I use local labor market conditions as an exclusion restriction to study the sensitivity of the results to different estimation techniques in a system of endogenous limited-dependent/qualitative variables. While all estimation methods lead to roughly the same qualitative conclusion, relaxing some of the underlying distributional assumptions in favor of semi-parametric (or less restrictive) methods generally leads to larger impacts than what I get with full maximum likelihood techniques. In conclusion, while previous work using U.S. data points towards somewhat ambiguous effects, the results here show a strong negative effect of working while in school on the probability of graduation, especially for men. This negative effect shows up both when I use a dummy for work activity while in school or when I use hours worked directly.

Mots-clés : abandon scolaire, conditions économiques locales, système d'équations simultanées avec variables dépendantes qualitatives/limitées, estimation semi-paramétrique

Keywords*:* *High school non-completion, local labour market conditions, system of endogenous binary or limited-dependent variables, semiparametric estimation*

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1 Introduction

Whether high school employment is beneficial or not has been extensively researched in the United States over the last two decades. Interest in this question arises in part from concerns that early work experience while enrolled in high school may hinder school performance and hence the accumulation of human capital. Others, however, have argued that early exposure to the labor market might actually lead young individuals to develop other aspects such as a greater sense of responsibility, better discipline, etc. In addition it is not clear that investments made early in work experiences may not provide long term benefits. For example, the inherent search process involved might help young people decide what they intend to do later. Moreover, some of the skills acquired on-the-job are likely to be transferable across employers and thus potentially help increase future wages.

While some of the earlier studies (e.g. Greenberger and Steinberg (1986)) tended to find relatively negative impacts, more recent work by Eckstein and Wolpin (1999), Oettinger (1999) and Ruhm (1997) showed that far from being the case that all work is detrimental, modest involvement in work activities actually lead to positive outcomes.[1] In particular, Ruhm found strong evidence that early work experience leads to higher future wages and better fringe benefits. Additionally, closer to this paper's focus, he finds that students working 10 hours per week during their senior year have a higher graduation probability from high school than those who do not work at all, although heavier work commitment is associated with a lower probability of graduation. Overall then, results are ambiguous regarding the impact of work while in school on educational attainment as measured by the high school graduation probability.

As pointed out by both Oettinger and Ruhm, early studies often suffered from the fact that work while in school was treated as an exogenous variable affecting other outcomes of interest. It is clear that such a strong assumption is likely to be violated. Ideally, one would like to be able to explicitly

[1] See Ruhm (1997) for an extensive literature review. While Ruhm focuses on future labor market outcomes, Oettinger (1999) analyzes the effect of work on educational performance through its impact on the grade-point average.

model the decision to work or the number of hours worked so as to treat both the educational attainment outcome and the hours worked outcome as representing a system of endogenous, possibly qualitative/limited-dependent, variables.

Although, as noted earlier, much work has been done on this issue using U.S. data, basically no such quantitative assessment has been carried out for Canada. Thus, the first objective in this paper is to examine, with Canadian data, the causal impact of working while in school on the decision to complete high school or not. The second goal pursued here is to assess whether the results are sensitive to the different estimation techniques used. Many alternative estimators are now available to applied researchers who wish to study problems involving jointly determined outcomes modeled either as dummy variables (graduating from high school or not/work while in school or not) or as a mixture of dummy and continuous variables (graduating from high school or not/hours worked while in school). Whether using alternative techniques makes a significant difference or not is something that would be useful to know.[2] I will thus use the context of estimating the impact of work while in school on the probability of graduating from high school as the vehicle for such a study of a system of limited-dependent/qualitative variables in the presence of an arguably credible exclusion restriction. More particularly, I will be interested in seeing whether relaxing the distributional assumptions associated with full maximum likelihood techniques leads to substantially different results. It is well known that while maximum likelihood techniques produce estimates which are consistent and asymptotically efficient under the null of a correct specification, semi-parametric techniques have the appealing feature of being more robust with respect to deviation from these assumptions.

The data used come from both the original 1991 wave of Statistics Canada's School Leavers' Survey (SLS) as well as the Follow-up in 1995. The original 1991 survey contains information on hours worked in the twelve months preceding the date of leaving school, either as a dropout or as a graduate.

[2] For examples of papers in which different tools do produce different results, see Blundell and Powell (2000) or Chay and Honoré (1998).

However, a non-negligible fraction of the individuals surveyed in 1991 were still enrolled in high school. Consequently, using the 1995 follow-up allows me to know whether those respondents graduated or not from high school and if they graduated, whether they entered into post-secondary education. Auxiliary data on the conditions of the local labor market in which these young individuals lived will be used as the main source of exogenous variation in work incidence (and intensity) while in school.

The results show that both men and women are sensitive to job opportunities that present themselves while they are enrolled in school and that, most clearly in the case of men, those job opportunities in turn lead to a reduction in the probability of graduating from high school. Note that the results for both samples contrast with the simple raw correlation between work incidence and graduation incidence, which is *positive*. These results are markedly different from the U.S estimates. In fact, this extra sensitivity of Canadians to the "treatment" consisting of working while in school may provide a partial explanation as to why the high school completion rate in the U.S has historically always been higher than in Canada: one of the mechanisms leading people to leave school before completion seems to have been much more important empirically in Canada than in the United States.

In addition, it is shown that relaxing some of the distributional and functional form assumptions associated with full maximum likelihood estimation makes a difference. More particularly, using linear IV methods tends to produce substantially larger estimated treatment effects compared to when I use a maximum likelihood bivariate probit model. This conclusion carries over when hours of work are used instead of the simple dummy for high school employment: using more robust semiparametric censored regression models produces larger treatment effects than is the case with the standard tobit. However, the size of the effect estimated with standard two-stage least squares appears unrealistically large.

The paper is structured as follows. First, I use the School Leavers Survey and its Follow-up to provide some evidence on the characteristics of the respondents by educational attainment. The next section then states the basic evaluation problem and provides a description of the methods used. Results are then presented and a discussion is provided on the possible reasons for the discrepancies in the results across estimation techniques. Concluding remarks follow.

2 The School Leavers Survey and its Follow-up (SLS)

In 1991, Statistics Canada collected information on the school and post-school labor market experiences of 9,460 young people aged 18 to 20. One of the main purposes of that survey was to estimate the high school completion rate. The original sample was drawn from the Family Allowances File, as they were the most complete listings of individuals under the age of 15 in Canada. Five years of Family Allowances Files were used to generate a sampling frame of 18-20 year-olds. Of the 18,000 individuals who were selected to be in the sample 10,782 were successfully traced and 9,460 responded. The interviews took place between April and June of 1991.

In 1994, Human Resources Development Canada[3] commissioned Statistics Canada to re-interview the same individuals in 1995. For that interview, the response rate was 66.8% as 6,284 individuals provided information on their schooling and labor market experiences. These individuals were thus aged 22 to 24 at the time of the re-interview and, as a consequence, the data are best suited for studying the early labor market experiences of the less educated among them.

The sample used includes 5,368 respondents from the Follow-up with no missing information on any of the relevant variables. I then create a dummy variable equal to one if each respondent has graduated from high school or not. The analysis is carried out separately for men and women.[4]

[3] A Government of Canada Department.

[4] Given that they were aged 18 to 20 at the time of the original interview in 1991, many were still enrolled in high school. Using data from the 1995 Follow-up allows me to use information at a time when the individuals should be well past their high school days. In fact, although there are respondents who report being enrolled in high school in 1995 (when they are between 22 and 24), the number of such cases is very small. Those observations were deleted. Also excluded from the sample are individuals who do not reside in one of the ten provinces. Although 40% of the individuals present in the School Leavers Survey Follow-up have at most a high school diploma, using the sample weights

The main source of arguably exogenous variation in work incidence (and intensity) while in school I use is a measure of the conditions prevailing in the local labor market in which these young individuals studied. More particularly, I use the unemployment rate in the Census Metropolitan Area if the individual studied in a CMA; otherwise I use the province average excluding the CMA's. Therefore,I have both cross-sectional differences in the unemployment rate in a given year and time differences within a particular region.

For those who do not complete high school, I use the unemployment rate that prevailed at the time (month) they quit school. For those who graduate, I use the annual average computed over the last four years by CMA or province. Note that whether or not the average is computed over a shorter period of time instead of four years does not make any qualitative difference.

2.1 Summary Statistics

Table 1 shows some simple descriptive statistics documenting the differences in individual characteristics by schooling attainment. In terms of family background variables, it seems clear that high school graduates come from families with better educated parents than is the case for dropouts (with no post-secondary education) and, also, they performed substantially better when they attended school, as reflected by the much higher proportion of individuals with a B grade point average or better. They also were less likely to have failed a grade in elementary school. This last piece of information suggests that, at least to a degree, poor performances in school precede the process by which students start to contemplate dropping out of high school, instead of the idea of dropping out subsequently affecting school performance.

It is interesting to note that the characteristics of the dropouts who did pursue post-secondary education are different from the characteristics of the

brings the estimated population proportion to about 30%, which corresponds closely to the percentage of individuals aged 25-26 in the (much larger) 1998 labor Force Survey who report having at most a high school diploma.

"real" dropouts on one important dimension: they are more likely to come from more educated families although they performed just as poorly in class. In fact, their parents are more educated than those of high school graduates. In terms of employment rates, dropouts with some additional post-secondary schooling are doing just as well as high school graduates.

Looking at the incidence of work while in high school and its relation to completion rates, we can see that in fact high school graduates were more likely to have worked than was the case for dropouts. Turning to hours worked while in school, Table 1 shows no evidence that, on average, more hours are associated with a lower incidence of completing high school. In fact, although not shown here, this is true over a substantial range in hours worked. This just serves to highlight the likely important effect of selectivity in the joint determination of hours worked while in school and high school completion.

Finally, Figures 1 and 2 show the distribution of hours worked while in school by gender. Note that this is the "conditional on positives" distribution. Two features are apparent in these pictures. The first one is the fact that the distributions tend to have long upper tails. Chay and Honoré (1998) have shown that this is an important source of misspecification in standard Tobit models. Additionally, the distributions very often do not exhibit a unique mode. This is particularly true for women. Indeed, Figure 2 is quite striking in that a substantially higher fraction of women dropouts worked about 40 hours a week in the twelve months preceding the date they left school compared to men. In general, the graph for the women who eventually dropped out exhibits peaks at twenty and forty hours of work (even thirty in Ontario). Again, we would expect differences between estimates from a standard Tobit model compared to ones obtained with the semi-parametric estimators due to such a significant deviation from normality.

3 The Evaluation Problem

Let y_i denote the outcome of interest for individual i, in this case high school graduation. We want to study the effect of a binary "treatment" d_i consisting of high school employment on the graduation decision. Let y_{i1} and y_{i0} define the potential outcomes for a given individual with and without the treatment. While we would naturally be interested in evaluating the true causal effect $y_{i1} - y_{i0}$, the usual identification problem consisting of not being able to observe the same individual in both states of the world makes this infeasible. Moreover, simple comparisons by treatment status do not provide an interpretable answer:

$$E(y_{i1}|d_i = 1) - E(y_{i0}|d_i = 0) = E(y_{i1} - y_{i0}|d_i = 1) - \{E(y_{i0}|d_i = 1) - E(y_{i0}|d_i = 0)\}$$

The first term on the right-hand side represents the effect of the treatment on the subpopulation that received the treatment while the second term indicates the magnitude of the selection bias. In the absence of random assignment of treatment status, this last term is typically non zero. For example, we might be worried that some students who are highly talented/motivated would also be more likely to work: potential employers may find these students relatively more attractive compared to the less talented. Thus, on the one hand, the probability of getting a job offer might be higher for these good students who are at the same time more likely to graduate. On the other hand, because they are better students, they can perhaps better afford to take time off schoolwork to pursue employment activities. All those unobserved (to the analyst) factors may play an important role.

Assuming we have a variable z_i whose effect on the outcome of interest is only through its effect on treatment status, we could implement an instrumental variable identification strategy. However, the fact that we are dealing with a system of two binary endogenous variables appears at first blush to pose a methodological problem. It is well known that the linear probability model (LPM) is flawed as a discrete choice model. its most serious flaw being that the predicted probability may lie outside the 0-1 interval. On the other hand it avoids imposing any particular distributional assumption, such as the one imposed by the bivariate probit model. One of the goals pursued in this paper is to examine to which extent, in this particular application, the estimates obtained from maximum likelihood methods such as the bivariate probit diverge from those obtained from IV-like methods, and to assess the likely sources for any discrepancy. The identification conditions defined below will prove useful for that purpose.

3.1 Identification of Causal Effects

In this subsection I borrow from Angrist (1991) and outline the conditions under which applying linear IV methods to a non-linear problem may yield a reliable estimate of the "true" causal impact in the presence of homogeneous effects.[5]

Letting, as before, y_i be the outcome variable for individual i (completes high school or not) and d_i be the treatment status indicator (works while in high school or not), let's define

$$E(y_i|d_i, u_i, z_i) = F(d_i, u_i; \beta)$$

$$E(d_i|u_i, z_i) = G(z_i, u_i; \gamma)$$

where z_i is a potential instrumental variable, u_i is an unobserved covariate, F and G are functions, and γ and β are parameters. As usual, it is assumed that the instrument z_i is independent of the unobserved component u_i and is correlated with the treatment indicator d_i. If these assumptions hold, then the average treatment effect is given by (Angrist (1991), p. 8):

$$\pi_1 = E[F(1, u_i; \beta) - F(0, u_i; \beta)] \tag{1}$$

Next come the crucial conditions for the identification of π_1 through instrumental variable estimation:

$$F(d_i, u_i; \beta) = f_1(d_i; \beta) + f_2(u_i; \beta) \tag{2}$$

[5] Below I come back on the meaning of a parameter estimated by IV methods in the presence of heterogeneous treatment effects. Note that in the present context I interchangeably use "IV" and "two-stage least squares" given that the model is just identified.

$$G(z_i, u_i; \gamma) = g_1(z_i; \gamma) + g_2(u_i; \gamma) \tag{3}$$

where f_1, f_2, g_1, and g_2 are functions. If either or both of these linear additivity conditions hold (in addition to the usual IV assumptions stated above), Angrist shows that the application of linear IV provides an estimate of the average treatment effect π_1. As pointed out by Angrist, although latent index models other than the LPM generally fail to satisfy these linear additivity conditions, many cumulative distributions are in fact almost linear over a range around the median. Therefore, linear IV is likely to provide a good approximation of the true causal impact when the variation in the outcome equation is close to the median. Under those conditions, the use of linear IV provides an attractive alternative to specifying, say, a full maximum likelihood bivariate probit with its implied arbitrariness in terms of the choice of the distribution. In other situations where the variation in the outcome equation is NOT in the neighborhood of the median, then we would expect the linear model not to perform quite as well.[6]

3.2 Treatment Effect in a Bivariate Probit

To model both the decision to complete high school and the decision to work in the twelve months preceding the end of going full-time to school, one can use a latent index framework such as the bivariate probit (see, e.g., Heckman (1978)). This model allows for the error terms of both choice equations to be correlated, as would be expected if some unobserved factors which influence the decision to drop out also influence the decision to work.

Let

$$y_i^* = x_i\beta + \delta d_i + \nu_i \tag{4}$$

$$y_i = 1(x_i\beta + \delta d_i + \nu_i > 0)$$

[6] Essentially, this is what Angrist finds in his Monte Carlo study. Interestingly, however, it turns out that while the linear IV model performs poorly with respect to the usual criteria (bias, RMSE, etc), so does the maximum likelihood bivariate probit model.

$$d_i^* = z_i\gamma + x_i\Gamma + \eta_i \tag{5}$$

$$d_i = 1(z_i\gamma + x_i\Gamma + \eta_i > 0)$$

where y_i denotes completion of high school, d_i is a dummy for work while in school, x_i and z_i are exogenous variables and (ν_i, η_i) follow a bivariate normal distribution $N(0, 0, \sigma_\nu^2, \sigma_\eta^2, \rho)$ where ρ is the correlation coefficient between ν and η. The exclusion restriction imposed is that the local unemployment rate affects the graduating decision only through its effect on working while in school.

Letting $\Phi()$ denote the standard normal cumulative distribution and letting $\widehat{\beta}$ and $\widehat{\delta}$ denote the standardized coefficients obtained from maximizing the likelihood function, the estimate of the average treatment effect $\widehat{\pi_1}$ is given by

$$\widehat{\pi}_1 = \frac{1}{N}\sum_i \left[\Phi(x_i\widehat{\beta} + \widehat{\delta}) - \Phi(x_i\widehat{\beta})\right] \tag{6}$$

3.3 Heterogeneous Treatment Effects

The interpretation of IV and of the bivariate probit model discussed above relies on the assumption of a constant effect across members of the population of interest. If that assumption is dropped, then the interpretation of the results obtained from using an IV identification strategy changes substantially. This is even more true in the case of a binary outcome.

Relaxing the constant effect assumption amounts to having to deal with a random coefficient model in which each individual has her/his own underlying π_i parameter. Using the terminology in Angrist, Imbens, and Rubin (1996), the population can be divided in groups defined by the contingent treatment indicator d_z. The *compliers* are those individuals for which we have $d_{z''} > d_{z'}$ when $z'' > z'$. For example, in the case of a binary instrument the compliers would be defined as those for which $d_1 > d_0$. Similarly, *always-takers* are defined by $d_{z''} = d_{z'} = 1$, *never-takers* by $d_{z''} = d_{z'} = 0$, and *defiers* by $d_{z''} < d_{z'}$ when $z'' > z'$. Of course, since only one of the potential treatment indicators is observed, we never actually identify which individuals belong to any one of those groups.

In the context of continuous outcomes, Imbens and Angrist (1994) provide identification conditions under which IV methods estimate what they label the "Local Average Treatment Effect" (LATE). Under those identifying conditions the LATE parameter represents the effect of the treatment for those whose treatment status is changed by the (binary) instrument. [7]

Now if we consider the case of binary outcomes, Abadie (2000) has shown that, generally speaking, standard Two-Stage Least Squares (2SLS) do not provide a best linear approximation to a non-linear causal relationship of interest. He then introduces an IV estimator for linear or non-linear models that has this property for models with a single binary instrument and which is based on a conditional-on-covariates version of the assumptions used by Imbens and Angrist (1994) to estimate average treatment effects with continuous outcomes.[8]

More particularly, one consequence of the Imbens-Angrist assumptions is that treatment is independent of potential outcomes conditional on belonging to the set of compliers (those whose treatment status is affected by the instrument). This further implies that, for compliers, comparisons by treatment status have a causal interpretation:

$$E(y_i|x_i, d_i = 1, d_{1i} > d_{0i}) - E(y_i|x_i, d_i = 0, d_{1i} > d_{0i}) = E(y_{1i} - y_{0i}|x_i, d_{1i} > d_{0i})$$

Abadie calls $E(y_i|x_i, d_i, d_{1i} > d_{0i})$ the Complier Causal Response Function (CCRF). Since we only observe one of the treatment indicator, d_0 or d_1, compliers cannot be individually identified. Abadie's main result is that

[7]Note the distinction between LATE and the effect of the treatment on the treated: in the latter case, the treated group includes both the compliers and the always-takers while in the former case, the effect is estimated only for the set of compliers.

[8]The Imbens-Angrist assumptions are: 1) the vector of potential outcomes and potential treatment assignments is jointly independent of the instrument z, and 2) a monotonicity condition which states that while the instrument may have no impact on some individuals, it must be the case that it acts in only one direction. In other words, the simultaneous presence of defiers and compliers in the population is ruled out.

expectations for compliers can be expressed in terms of expectations for the whole population. More particularly, suppose one chooses β and δ to minimize

$$E[(E(y_i|x_i, d_i, d_{1i} > d_{0i}) - x_i\beta - \delta d_i)^2 | d_{1i} > d_{0i}] \tag{7}$$

As such this minimization problem is not feasible, precisely because the set of compliers can not be identified. However, Theorem 3.1 in Abadie (2000) shows that:

$$E[\kappa_i E(y_i|x_i, d_i, d_{1i} > d_{0i}) - x_i\beta - \delta d_i)^2]/Prob(d_{1i} > d_{0i}) =$$

$$E[(E(y_i|x_i, d_i, d_{1i} > d_{0i}) - x_i\beta - \delta d_i)^2 | d_{1i} > d_{0i}] \tag{8}$$

where

$$\kappa_i = 1 - \frac{d_i(1 - z_i)}{1 - E[z_i|x_i]} - \frac{z_i(1 - d_i)}{E[z_i|x_i]}$$

The minimization problem of equation (7) is now rewritten in terms of estimable quantities. Note that although it is represented as a linear function, any sort of functional form that is convenient for a given problem can be used as well. More particularly, given that the outcome is a binary variable, it may be more suitable to use a normal parameterization and minimize instead

$$E[\kappa_i E(y_i|x_i, d_i, d_{1i} > d_{0i}) - \Phi(x_i\beta - \delta d_i))^2] \tag{9}$$

where $\Phi()$ is the standard normal cumulative distribution, so as to reflect the discrete nature of the outcome. In any case, the solution to minimizing either equation (8) or equation (9) gives us an approximation of the true Complier Causal Response Function.

A few remarks are in order here. First, this solution to approximating the CCRF works only with a single binary instrument. Secondly, one could still use 2SLS and interpret the resulting estimate as approximating the CCRF provided that $E[z_i|x_i]$ is *linear*. With continuous covariates, this condition cannot be fulfilled in a non-linear model. With discrete covariates it can, provided that the model is fully saturated. Clearly, this is workable only when one has either very few covariates (or many can be safely considered ignorable), or a very large sample.

In this particular application, in order to experiment with this methodology, I created a binary instrument indicating whether one lives in a low unemployment area or not. There are at least two reasons to view the results with caution. One is the fact that the choice of the cutoff is totally arbitrary.[9] The second is that by creating basically just two groups, the ones living in low unemployment areas vs. the others, the coefficient's standard errors are likely to suffer from a downward bias if people living in low unemployment areas share a common component of variance (Moulton (1986)).[10] Note that to reflect that fact that κ_i is estimated, standard errors were estimated using the bootstrap with 100 replications.

To emphasize again, given that I do not have an "ideal" candidate binary instrument, the results should be viewed with some caution although assessing the relative performance of this estimator in the context of a real application should still be of interest.

3.4 Estimating Treatment Effects with a Censored Endogenous Regressor

In this subsection, I will directly make use of the number of hours worked reported by the individuals instead of dichotomizing it into a work/no work endogenous binary regressor. So the substantive question of whether high school students' educational attainment is affected by work while in school is refined somewhat by framing it in terms of the impact of an additional

[9] I basically chose the cutoff point such that all methods "would work" in the sense of the effect of local labor market conditions going in the same direction as in the variable treatment case and of being roughly of the same magnitude.

[10] Note that this problem gets worse the lower is the number of groups and the larger is the number of people per group. Strictly speaking, I faced the same problem when using the unemployment rate directly. However, the number of groups was very large (over 600 distinct values for the unemployment rate), and the number of people per group was accordingly relatively small.

hour worked on the probability of completion.

If basically everyone worked, the evaluation problem would be relatively simple (at least in a constant treatment effect world). In its simplest form, one could use a linear regression to study the effect of local labor market conditions on the number hours worked and then use the fitted values from that model to obtain a causal impact with, for example, a probit.

The complication here arises from the fact that not everyone works. Consequently, one must explicitly account for the censoring at zero hours. Two basic approaches are pursued here. First I estimate a bivariate Probit/Tobit model building on the assumption of joint normality.

More specifically, let the latent propensity to complete high school and the number of hours worked be represented again as:

$$y_i^* = x_i\beta + \delta h_i + \nu_i \tag{10}$$

$$y_i = 1(x_i\beta + \delta h_i + \nu_i > 0)$$

$$H_i = max(0, z_i\gamma + x_i\Gamma + \eta) \tag{11}$$

where h_i represent the number of hours worked, x_i is the same vector of exogenous variables as in the previous model and z_i is the same instrument, and the error terms ν and η are again assumed to follow a bivariate normal $N(0, 0, 1, \sigma_\eta^2, \rho)$. In estimating equations (10) and (11), I again make use of the assumption that local labor market conditions affect the decision to complete high school only through their effect on the number of hours worked.[11]

As is well known, the standard tobit model relies on the assumption that the error term is normally distributed. It also assumes homoscedasticity. However, recent work by Kenneth Chay and Bo Honoré (Chay and Honoré (1998)) in an application focusing on the effect of Civil Rights Legislation on the economic status of African-Americans has shown that departures from normality can lead to large biases in the maximum likelihood estimates.

[11] See the Appendix for a full derivation of the likelihood function.

More specifically, Chay and Honoré find that long tailed distributions are a particular source of biases.

As we saw in the previous section, the distribution of hours worked by high school students does show a substantial departure from normality. It would therefore appear to be appropriate to relax the assumption of normality. Two semiparametric estimators will be used to model the number of hours worked in the first stage of the estimation, the censored least absolute deviation (CLAD) (Powell (1984)), and the symmetrically censored least squares estimator (SCLS) (Powell (1986)). The basic idea of the CLAD is to exploit the fact that the consistency of the parameters estimated with a Least Absolute Deviation criterion model is not sensitive to censoring (and heteroscedasticity) whereas they are under a least-squares minimization criterion. As for the SCLS, it relies on the observation that absent any censoring, the error term distribution would be symmetric.[12] The censoring mechanism destroys this symmetry by chopping off the lower tail, for example. By appropriately trimming the other (uncensored) tail of the distribution, symmetry can be restored and consistent estimates of the parameters of interest can be obtained.[13]

It is worth pointing out that the SCLS is more restrictive in terms of the underlying error process than is the CLAD. More particularly, although the error term need not be normally distributed, the assumption of symmetry of the distribution is retained, which is not the case for the censored least absolute deviation estimator, which requires only that the error term to have zero mean, conditional on x_i and z_i. Again, a quick look at the empirical distribution of hours worked suggests that the symmetry condition is likely to be restrictive.

After estimating the effect of local labor market conditions on hours worked, the resulting fitted values are then plugged into the outcome equation. As usual with such "Two-Step" methods, standard errors need to be

[12] Assuming of course, at the start, that the underlying error term was assumed is symmetrically distributed.

[13] For a good description of both of these methods, see Chay and Honoré (1998), pp. 13-16 or DiNardo and Johnston (1997), pp. 442-446. See also Paarsch (1984) for a Monte Carlo evaluation on the performance of the CLAD vs Tobit.

adjusted for the fact that estimated values are used as a regressor. While such an adjustment is straightforward in a linear model, the fact that I am using a semi-parametric first step would complicate considerably the computation of the asymptotic standard errors. Consequently, I again rely on the bootstrap to compute the standard errors.

4 Results.

4.1 Both Outcomes Modelled as Binary Variables

As shown in the first two columns of Table 2, ignoring the endogeneity of having a job and simply using a Probit or a linear probability model would lead us to conclude at the absence of any negative effects on the probability of completing high school. This, of course, is simply the conditional-on-observables version of what we saw in the descriptive statistics. Indeed, the coefficient associated to having a job is not only positive but it is also statistically significant for women.

However, recognizing the endogeneity of work activity substantially changes the results. As we can see, using either a linear two-stage least squares approach or the full maximum likelihood bivariate probit not only reverses the sign associated to the "Had a Job" dummy, but points to large treatment effects.[14] In the context of the constant treatment effect assumption, working while in school is predicted to decrease the probability that men graduate from high school by about 28% in the case of the bivariate probit and 63% by 2SLS. Although a large part of the appeal of instrumental variable methods, as applied to non-linear problems, lies in its absence of distributional assumptions, we saw in Section 3 that certain conditions had to be fulfilled for IV methods to accurately approximate the "true" causal effect. One of those conditions was that the variation in the outcome equation should be around the median, where most cumulative distribution functions are approximately linear. Using the estimates from the bivariate probit model, it

[14]Note that all coefficients reported in the tables are marginal effects coimputed at the mean of the regressors.

turns out that turning the "had a Job" dummy on results in making the latent index distribution shift from 0.65 to 0.91. Hence, it appears that the 2SLS results should be viewed with some skepticism as this sort of movement is well away from the median of the latent index distribution. Note that in relative terms, the difference in the results obtained with the two methods is even larger for women.

To investigate possible sources of discrepancy between 2SLS and bivariate probit, I used combinations of these two models. Namely, I ran a linear first-stage followed by a standard probit second stage. I also ran a probit first-stage followed by a linear second stage. In the latter case, the estimated treatment effect is -0.49 and -0.42 in the former case. Therefore, in this application, functional form assumptions seem to play a role in both stages.

On the whole, again in the context of assuming constant treatment effects, it would appear that the results obtained using 2SLS are excessively large. Although the bivariate probit also fails to satisfy the linear additivity identification conditions outlined in Section 3, it would seem to produce more credible estimates when one moves away from the median of the latent index distribution.[15]

Turning to Table 3 and to the use of the local unemployment rate dichotomized into a High/Low indicator[16], we can see that although the results for the bivariate probit are fairly similar to the ones reported in Table 2, the ones for 2SLS are even more implausible than before as they imply that

[15] In a recent paper, Angrist (2001) suggests that the use of linear IV methods for systems of binary outcomes has the added benefit that it is robust against misspecification of the first stage. Citing Kelejian (1971), Angrist notes that "in the context of an additive constant-effects model [...], second stage estimates computed by OLS regression on first stage fitted values from a nonlinear model are inconsistent, unless the model for the first stage conditional expectation function (CEF) is actually correct. On the other hand, conventional 2SLS estimates using a linear probability model are consistent whether or not the first-stage CEF is linear." In the same *Journal of Business and Economic Statistics* issue though, Imbens (2001) argues that this benefit of the LPM appears to him "largely illusory" given the fact that "statistical modelling is only intended to provide flexible approximations to the underlying conditional distributions" which, he remarks, "is a fundamentally different role from that played by the substantive assumptions [...] essential for identification."

[16] Local labor markets with an unemployment rate below 6.5% were classified as low unemployment areas and the others as high unemployment areas.

holding a job while in school should decrease the probability of graduating by over 200%!. However, dropping the assumption of additive constant effects and turning to heterogenous treatment effects, the very high estimates obtained with 2SLS with either form of the instrument may not be such a bad approximation for the effect on the subsample of individuals who were induced to take a job by the fact that they were living in a tight labor market.

Work by, e.g. Solon, Barsky, and Parker (1994) on the cyclicality of real wages has shown that the composition of the work force changes substantially with the business cycle. Basically, when the economy is booming, "everyone can get a job" while in downturns, only the better workers keep their jobs. In the present context, the very high 2SLS estimates reported in both Table 2, and especially in Table 3, may indicate that the set of compliers may have been particularly "sensitive" to job market opportunities that would allow them to leave school, where they may have been struggling. In other words, the better students who had a job but not really because they happened to be living in a low unemployment rate area would not be part of the set of compliers.[17]

However, as pointed out in Section 3, linear IV methods do not, in general, approximate the Compliers Causal Response Function. To approximate such a function, I used Abadie's "Causal IV" estimator, both with a linear response function and nonlinear (normal) one.[18] As it turns out, the results are much closer to the ones obtained with a bivariate probit. In fact, they are almost identical for men in the case of the nonlinear response function. These results have a robust causal interpretation and measure the effect of the treatment on the set of compliers. For women, the differences in the estimates are fairly substantial but the results are not that informative, basically because the instrument is only imprecisely related to having a job.

[17] This is just hypothesizing, of course, but it really gets at the substantive question of what it means to be "induced by the instrument". As pointed out by Heckman (1997), people act on their private information and the set of people who were induced to take a job by the favorable economic conditions may have done so because it may simply have been a case where those individuals' comparative advantage was to work and not be in school.

[18] I use the bootstrap on the whole system to estimate the coefficients' standard errors.

Consequently, the identification strategy breaks down somewhat.

Overall the results seem to suggest that, for this application at least, standard linear IV methods applied to nonlinear problems in which there is substantial variation in the distribution of the latent index away from the median may provide poor approximations of the "true" effects.

4.2 Outcomes Modelled as a Mixture of Binary and Limited-Dependent Variables.

Table 4 reports estimates of the impact of an additional hour of work on the probability of graduation, using again the local unemployment rate as an instrument. As before, all estimates are marginal effects. We saw in Figures 1 and 2 that the distribution of hours worked showed a substantial departure from normality which may warrant the use of methods more robust to deviations from normality than the standard Tobit.

The basic conclusion to be drawn from Table 4 is that, indeed, using semi-parametric methods makes a difference in modeling the determination of hours worked. In all specifications, the bivariate probit/tobit appears to suffer from a large downward bias. In the case of men, the estimate is more than twice as small compared to the next smallest one (which results from using a censored least absolute deviation first stage). As one would expect when using semiparametric techniques, the precision of the treatment effect estimates is lower than with the maximum likelihood.

For women the difference in the coefficients is even more striking: the bivariate probit/tobit reveals an extremely imprecise effect of the instrument on hours worked, which naturally affects the estimate of the treatment effect. All other estimation techniques point towards larger treatment effects. However, the precision of the estimates appears to be more of a problem for women than it is for men, especially in the case of both the OLS/probit and the SCLS models.

Interestingly, the OLS/Probit results are closer to the ones obtained with either SCLS or, especially, CLAD than they are to the maximum likelihood estimates. In this application, it seems to be a lesser evil to ignore altogether the censoring problem and use OLS than to take censoring into account through a full blown maximum likelihood approach relying on the normal distribution.[19]

Using the results with the semiparametric regression models, it is possible to provide a rough indirect assessment of the validity of the estimates when using a simple dummy for work activity. The results for men using the CLAD model as a first stage show an average marginal effect of about -0.8% per hour. Given that men work an average of a little over 13 hours per week, this would give us an average estimate of about -10.4% on the probability of graduation. However, this assumes a constant marginal effect. Although not shown here, the marginal treatment effect, perhaps not too surprisingly, declines more or less monotonically with hours worked. At 5 hours per week, for example, and evaluating all other regressors at their means, the marginal treatment effect is about -3% and falls to below -2% at ten hours. But even if I use the effect evaluated at 5 hours and multiply it by average hours, I still get an estimated average treatment effect of working of about -40%, which is much closer to the effect estimated with the bivariate probit (and Abadie's causal IV) than it is to the standard 2SLS estimates. These calculations are simply intended to provide a rough "test", but they do point towards the conclusion that 2SLS applied to a system of binary regressors may produce unreliable estimates when the conditions for 2SLS to be an adequate approximation to the average treatment effect are not satisfied.

In summary, it seems that excluding local labor market conditions from the graduation outcome reverses what simple descriptive statistics would lead us, in fact, to conclude: working does seem to have the causal effect of making young Canadian students drop out of high school. Interestingly, although Cameron and Heckman (1994) show that young people in the United States (using the NLSY) exhibit some sensitivity to an alternative measure of local labor market conditions, recent attempts by Ruhm (1997) and Oettinger (1999) at trying to use the local rate of unemployment as an instrument for work while in school to explain either educational attainment or high school

[19]Interestingly, in another application, Chay and Honoré (1998) basically come to the same conclusion.

performance have failed in that the instrument appears to be rather weak, contrary to the case here.

Finally, to assess whether excluding the local unemployment rate from the outcome equation is acceptable, I performed an overidentification test by using three local labor market measures as instruments: the local unemployment rate used throughout the paper as well as the provincial unemployment rate for individuals aged 25-44 and the overall provincial unemployment rate. More specifically, I regressed the residuals obtained from the structural equation (using the parameters estimated by IV) and regressed them on the excluded instruments in addition to the other exogenous variables. Under the null hypothesis that the exclusion restrictions are valid, the R-squared from such a regression times the number of observations converges to a χ^2 distribution with degrees of freedom equal to the difference between the number of instruments and the number of parameters estimated.

As it turns out, the value of the χ^2 statistic is equal to 1.39 for men, which easily passes the overidentification test. For women, though, it is equal to 30.97, which makes the identification strategy look suspicious.[20]

5 Conclusion

In this paper I find that high school students in Canada, particularly men, are sensitive to the state of the local labor market and that the jobs they take up while they are still in school cause a significant decrease in their graduation probability. This is in contrast to much of the evidence in the United States. It thus provides a partial explanation as to why the high school dropout rate in Canada has always been higher than in the U.S.[21]

[20] As emphasized in DiNardo and Johnston (1997), the test is not about whether all instruments are valid but only about whether given that one is valid, are the additionnal ones valid too. In this case, however, the fact that the instruments all try to measure the same thing implies that if the additional ones are deemed appropriate then one can probably be more confident about the validity of either one of the three in a just-identified model.

[21] Even if the institutional environment is not quite the same in both countries with, e.g, the Province of Québec requiring only 11 years of schooling to get a high school diploma, the historical differences in the dropout rates of the two countries have been substantial

In addition, it is shown that the magnitude of the estimated effect varies quite a lot across estimation techniques. Overall, the estimated effects of working while in school on the probability of graduation obtained with full maximum likelihood were always the lowest ones. While they appeared to be quite reasonable in the cases where I used only a dummy variable for holding a job, the maximum likelihood estimates did not perform quite as well once I used hours of work directly. Departure from normality, at least in this application, appears to be a serious problem affecting the consistency of the maximum likelihood estimates when estimating the effect of hours worked on the probability of graduating.

In light of the results obtained in this paper, one may be left to wonder why Canadians are more sensitive to local labor market conditions as a channel leading to not completing high school than are Americans. A possible explanation worth investigating may be that basically all wage differentials are smaller in Canada, including the wage premium to holding a high school degree. In fact, although not reported here, computation of the average wage gap for full-time workers aged 16 to 24 between those with just a high school diploma and those without one using the 1996 Canadian Census results in there being fundamentally no difference. Such is not the case in the U.S. (Krueger (1997)). Consequently, it may not be surprising that Canadians may display a stronger tendency to be "on the lookout" for jobs that would serve as a vehicle for a more or less permanent transition to the labor force before graduating from high school. They might simply realize that if they are going to stop anyway after high school, there is little reason to wait after graduation in the hope of getting a better wage. Naturally, these comparisons of mean wages may simply mask a different selection process in the two countries which could affect the relative quality of the pool of workers without a high school diploma.

enough that differences in institutions cannot really have been a major contributor.

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Appendix

Let the bivariate normal density function be expressed as:

$$f(\nu_i, \eta_i) = \frac{1}{2\pi\sqrt{1-\rho^2}\sigma_\eta} \exp\left[-\frac{1}{2(1-\rho^2)}\left(v_i^2 - 2\rho v_i \frac{\eta_i}{\sigma_\eta} + \frac{\eta_i^2}{\sigma_\eta^2}\right)\right] \quad (12)$$

Each individual's contribution to the likelihood function can be expressed by examining all possible cases, where y_i denotes high school completion and H_i: represents the hours worked by individual i:

$$P(y_i = 1, h_i > 0) = \int_{-x_i\beta - \delta h_i}^{\infty} f(v_i, \eta_i)\, dv_i \quad (13)$$

Standardizing the bivariate normal density function:

$$P(y_i = 1, h_i > 0) = \int_{-x_i\beta - \delta h_i}^{\infty} \frac{1}{\sigma_\eta} \phi_2(v_i, \eta_i^*)\, dv_i, \quad (14)$$

where ϕ_2 corresponds to the standardized density and $\eta_i^* = \frac{h_i - z_i\gamma - x_i\Gamma}{\sigma_\eta}$. In similar fashion:

$$P(y_i = 0,\ h_i > 0) = \int_{-\infty}^{-x_i\beta - \delta h_i} \frac{1}{\sigma_\eta} \phi_2(v_i, \eta_i^*)\, dv_i. \quad (15)$$

The last two cases are:

$$P(y_i = 1,\ h_i = 0) = \int_{-x_i\beta}^{\infty} \int_{-\infty}^{\frac{-z_i\gamma - x_i\Gamma}{\sigma_\eta}} \phi_2(v_i, \eta_i^*)\, dv_i d\eta_i^*, \quad (16)$$

and

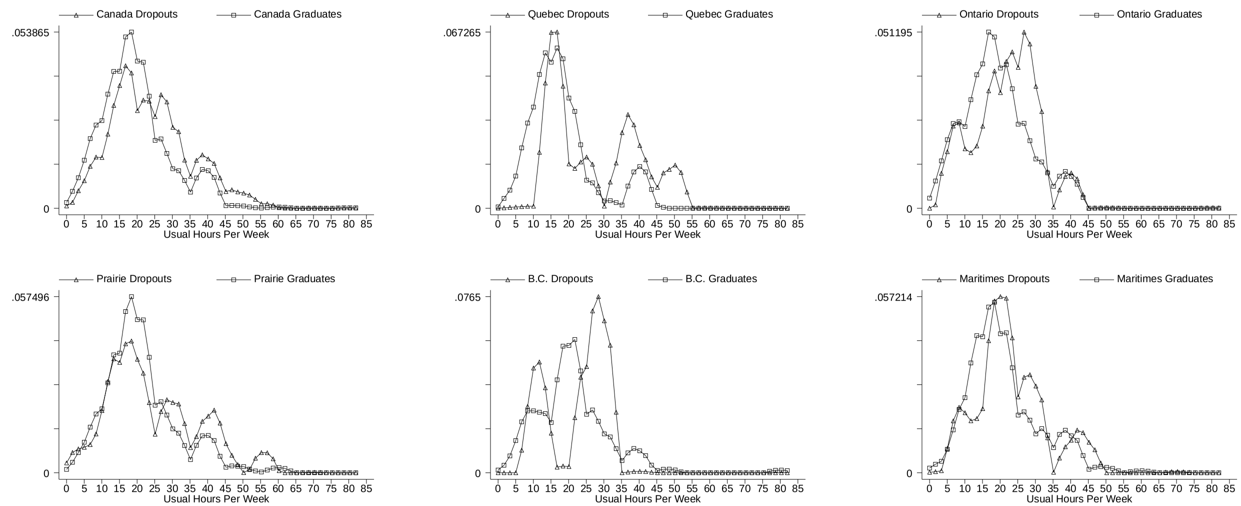
$$P\left(y_i=0,\, h_i=0\right)=\int_{-\infty}^{-x_i\beta}\int_{-\infty}^{\frac{-z_i\gamma-x_i\Gamma}{\sigma\eta}}\phi_2\left(v_i,\eta_i^*\right)dv_i d\eta_i^*=\Phi_2\left(-x_i\beta,\frac{z_i\gamma+x_i\Gamma}{\sigma_\eta}\right), \tag{17}$$

where Φ_2 corresponds to the standardized cumulative bivariate distribution.

Letting n_j $(j=1,4)$ represent the number of observations in each subsample corresponding to the cases just described, we obtain the following log-likelihood function which is maximized with respect to the parameters $\beta,\Gamma,\delta,\gamma,\sigma_\eta$ and $\rho:$

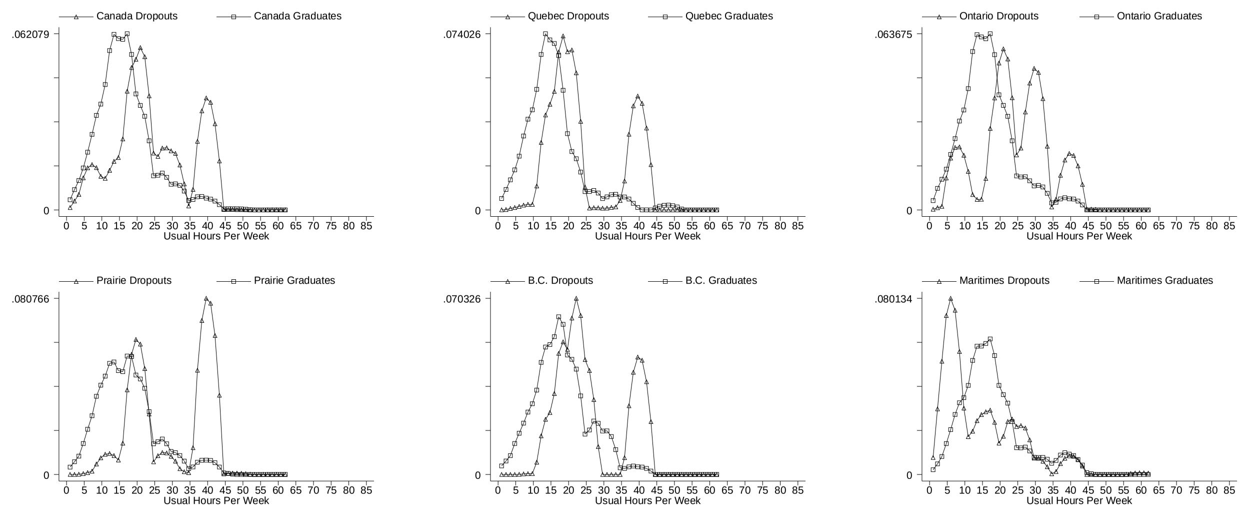
$$\log L=\sum_i^{n_1}\log\int_{-x_i\beta-\delta h_i}^{\infty}\frac{1}{\sigma_\eta}\phi_2\left(v_i,\eta_i^*\right)dv_i+\sum_i^{n_2}\log\int_{-\infty}^{-x_i\beta-\delta h_i}\frac{1}{\sigma_\eta}\phi_2\left(v_i,\eta_i^*\right)dv_i \tag{18}$$

$$+\sum_i^{n_3}\log\int_{-x_i\beta}^{\infty}\int_{-\infty}^{\frac{-z_i\gamma-x_i\Gamma}{\sigma\eta}}\phi_2\left(v_i,\eta_i^*\right)dv_i d\eta_i^*+\sum_i^{n_4}\log\Phi_2\left(-x_i\beta,\frac{z_i\gamma+x_i\Gamma}{\sigma_\eta}\right)$$



Source: School Leavers Survey

Figure 1. Distribution of Hours Worked While in School-Men



Source: School Leavers Survey
Figure 2. Distribution of Hours Worked While in School-Women

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