Parental Income Shocks and the Education Attendance of Youth

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Abstract

In this study I find that parental income shocks that occur at the time of high school completion have significant negative impacts on the education attendance of youth. Parental job loss, which results in family income reductions that persist over time, is particularly important. This alarming evidence of the consequences of labour market dislocation has received little prior attention. My results highlight the importance of financial constraints on post-secondary education attendance of youth, and support the case that parental income has a significant causal effect on the education outcomes of youth. I employ longitudinal information on youth from the Canadian Survey of Labour and Income Dynamics (SLID) to conduct this analysis. I estimate a full year-to-year grade transition model to uncover the immediate and lagged causal impacts of parental job loss on education attendance. These shocks lead to both a greater likelihood of dropping out of high school and lower rates of university entry.

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1 Introduction

Education attainment is a significant determinant of an individual's economic well-being. The wage premium paid to university educated workers is large and has risen in North America over the past several decades. If opportunities for obtaining a university education are related to parental income, rising university wage premiums may lead to increasing levels of intergenerational income inequality (Fry, Turner and Carnevale (2000)).

There is overwhelming evidence that education attainment is positively correlated with the income levels of parents (see Section 2 for details). Youth from families with high income parents are much more likely to attend university in both the US and Canada. This correlation may not reflect causality, however, if there are characteristics of parents which impact both parental income and the education attainment of children. These characteristics may include parental ability, diligence, mental health, dependability, culture and individual preferences. Government policies intended to alter parental income levels may not have the desired impact on youth education outcomes if the relationship is not causal.

Parental income may directly (causally) impact post-secondary education attendance in at least two ways. Transfers from parents may assist youth to finance post-secondary education attendance. Youth from low income families may be constrained in their ability to obtain this type of assistance. Governments often fund student financial aid programs (using grants and loans) to reduce any financial constraints on post-secondary attendance. Secondly, parental income may be spent on increasing investments in child learning outcomes at the elementary, secondary and pre-school levels, increasing the preparedness of youth for post-secondary study.

Several recent studies (Shea (2000), Mayer (1997), Levy and Duncan (2000), Blanden and Gregg (2004)) have concluded that the causal impact of parental income on education outcomes is small or even zero. These studies have employed a variety of techniques to uncover causal impacts. These techniques often employ movements in parental income over time within families for identification. Many such income movements or shocks may only be temporary, hampering the ability to identify the underlying impact of parental income on attendance.

One method to overcome this identification problem is to separate out parental income shocks which are persistent, and to examine the impact of these persistent shocks on education attendance. I take this approach to identification in this paper. I employ exogenous parental job loss to identify these persistent income shocks. Jacobson, LaLonde and Sullivan (1993) and others have clearly illustrated the persistent impact that exogenous job losses have on income levels. Exogenous job loss is defined as job loss due to redundancy, employer business failure or employer dismissal.

The analysis I conduct employs 1993-2001 data on individual youth from the Canadian Survey of Labour and Income Dynamics (SLID). The particular advantage of this data is the ability to measure parental income shocks, and then to analyze the impact of these shocks on the subsequent annual education attendance outcomes of youth. I focus on shocks that occur at the time of normal high school completion, when youth are 16 to 18 years old. Education outcomes of youth are then analyzed from age 16 up to age 19 or 20. At age 16, the vast majority of youth are still in high school, and have yet to make their own decisions about education attendance. By age 19 or 20, youth have had the opportunity of acquiring the prerequisites for university entry.

The information required for this analysis does not co-exist in the major representative micro data sets employed to analyze the education decisions of youth in the U.S. The Panel Study of Income and Dynamics (PSID) does not have detailed year to year education enrollment information for young adults. The National Longitudinal Study of Youth (NLSY) does not collect annual parental income and labour market outcome information for all youth of school-leaving age[1]. To my knowledge, there exist no studies of the causal impact of parental income shocks, particularly persistent shocks caused by job loss, on the immediate subsequent education attendance decisions of youth.

To identify the causal impact of parental income shocks on education attainment, it is important to control for those attributes of parents that impact both education attainment of children and parents' own labour market outcomes. I estimate standard discrete choice models of post-secondary education attendance controlling for a large number of parental, family and individual characteristics. I find that persistent negative parental income shocks attributable to exogenous job loss have significant negative impacts on university attendance. A persistent ten thousand dollar drop in annual parental income lowers the probability of a youth attending university by nearly seven percentage points. A temporary drop of the same magnitude lowers this probability by only around one percentage point. This evidence points to an alarming impact of labour market dislocation that has received little attention to date. Government intervention on behalf of affected youth may be warranted in these situations on both equity and efficiency grounds.

The finding that these income shocks affect education attendance, even after controlling for parental education and average income levels, provides strong evidence that parental income has causal impacts. It also points to the existence of significant financial constraints on attendance, and the importance of transfers from parents in the education attendance decision. These negative impacts occurred despite the availability of government-subsidized student loans for less-advantaged youth. If credit constraints (the ability to borrow) alone precluded youth from attending, parental income shocks that occur at the time of high school

[1]Parental income information is not collected for youth who leave the parental home.

completion should not impact attendance when loans are available.

Individual investments in higher education are risky, and individual preferences for assuming large debt loads at young ages may be quite heterogeneous across the population. Many youth may be averse to borrowing large amounts to invest in their own human capital even if the expected payoff appears large. There are several risks involved, including course completion risk and wage premium risk. Relaxing credit constraints may not be sufficient to ensure all youth can attend post-secondary education.

In addition to the standard discrete choice models of post-secondary education attendance discussed above, I estimate a model of the complete set of annual education outcomes for youth from age 16 to age 19 or 20. Each annual education transition is analyzed to determine whether shocks lead to immediate high school dropout behaviour or have lagged effects on university or community college entry. The full set of education transitions are analyzed in a framework that imposes the natural sequential constraints on education attendance. For example, youth must first complete high school to attend university. In particular, I estimate a full year-to-year age and grade transition model using the technique employed by Cameron and Heckman (2001). The longitudinal data in the SLID is ideal for estimation using this technique, and including parental income shocks is a considerable extension of the Cameron and Heckman analysis. The results show that persistent parental income shocks measured by job loss lead to both increased high school dropout behaviour and to lower rates of university entry even for those youth who complete high school.

The grade transition model estimates provide a direct test of the exogeneity of parental job loss, providing further evidence that I am uncovering a causal impact of parental income[2]. I include job loss shocks that occur after an education outcome is observed into the estimated model to control for any potential unobserved parental characteristics related to these shocks.

[2]The concern here is that job loss itself may reflect unobserved characteristics of parents.

These additional shock measures were not statistically significant, and their inclusion did not change the estimated negative impacts of the correct job loss shocks on education outcomes.

The outline of the paper is as follows. A review of the relevant literature is provided in Section 2. An economic model of the education decisions of youth which focusses on the role of parental income is described in Section 3. The SLID micro data set is described in Section 4, along with a description of Canadian post-secondary education system. Standard reduced form estimates of the impact of parental income shocks on the post-secondary education attendance of youth are presented in Section 5. The full year-to-year grade transition model is discussed in Section 6, along with simulations of the impact of parental job loss on education attendance. Section 7 concludes with a short discussion of the main results.

2 The Literature

The relationship between parental income and the education outcomes of youth has received considerable attention in social science and public policy research. Education attainment is strongly related to family background, particularly to parental characteristics, in the vast majority of countries. Shavit and Blossfeld (1993) put together studies documenting this relationship for 13 countries, including the U.S. and Canada. There is a vast U.S. literature on the determinants of the education attainment of youth. Many examples are given in the survey of Haveman and Wolfe (1995). Duncan and Brooks-Gunn (1997) compile twelve studies of the consequences of growing up in poverty in the U.S. on youth outcomes. One of the main conclusions drawn from this research is that parental income is positively associated with the education attainment of their children, but the measured impact varies from study to study and is not always economically large. Recent research has been concerned with uncovering the causal impact of parental income on educational attainment.

Shea (2000) attempts to uncover the causal impact of father's income on the completed years of education of US youth. He employs job loss, union status and industry of employment of parents as instruments for parental income in a two stage procedure. Variations in parental income caused by what Shea considers as "luck" rather than ability were thus employed to uncover causal impacts. Results from OLS showed a significant impact of father's income on education levels. The two-stage estimates showed no causal impact, except if the father has low education. In this study, I employ job loss as an indicator of a more permanent parental income shock rather than an instrument for income levels. I can also observe the immediate impact of shocks on education attendance rather than looking at completed years of schooling by individuals in their mid-twenties.

Mayer (1997) employs several strategies to identify the causal impact of parental income on a large set of outcomes of U.S. children and youth, including education attainment. One of several strategies employed to uncover the causal impact of parental income was to include a measure of parental income received after the youth's educational outcome as a control for the unobserved characteristics of parents affecting both income and youth outcomes. This strategy resulted in only a small causal impact of parental income on years of schooling by age 24 being identified[3]. Levy and Duncan (2000) employ a siblings fixed effects strategy to control for unobserved parental characteristics in an attempt to identify causal impacts. They find small impacts of income during childhood and adolescence. Both these studies use variations in income within families over time to identify causal impacts. If most income variations are temporary, it is not surprising that small causal impacts were found.

Cameron and Heckman (2001) estimated a sequential age and grade transition model of education attainment using data from the NLSY. A statistically significant impact of parental

[3]Mayer also found a significant negative impact of parental income drops measured by year to year drops of 35 % or more on years of schooling.

income on college attendance was found in initial estimates. Once the model was expanded to include Armed Forces Qualifying Test (AFQT) scores, however, parental income no longer had a statistically significant effect. The authors interpret this finding as evidence that short term liquidity constraints play no significant role in college attendance decisions and claim tuition subsidies should have no appreciable impact on inequality in college attendance. Early learning outcomes are much more important, so policies aimed at earlier youth outcomes will have a larger impact on inequality in education attainment. I employ the Cameron and Heckman estimation strategy in Section 6, but do not include test score information. I also include measures of parental income shocks.

Keane and Wolpin (2001) also show that the parental income-education attainment relationship is compatible with a model where borrowing constraints have little impact on college attendance. Borrowing constraints do, however, have a large impact on hours of work and consumption levels while youth are in college. The authors argued against including AFQT scores in estimation. Test scores may actually reflect future expected borrowing constraints, as effort while in high school (which increases AFQT scores) may be related to future education opportunities. Keane and Wolpin (1997) found that college tuition subsidies can change behaviour in high school, increasing high school attendance rates.

Using Canadian data, Corak, Lipps and Zhao (2004) analyzed the relationship between family income and attendance of youth at universities and colleges with information from the Survey of Consumer Finances (SCF)[4] and the General Social Survey (GSS). Family income and university attendance are strongly related, but there was no evidence of a strengthening in this relationship in Canada as a whole over the late 1990s. This study updated the results of Bouchard and Zhao (2000) using the GSS for 2001. The relationship between parental income

[4]The analysis using the SCF updated and improved upon earlier work by Christofides, Cirrello and Hoy (2001).

and education attainment did strengthen from 1986 to 1994 in the GSS data. No attempt was made to uncover the causal impact of parental income on education attendance in these studies for Canadian youth.

The Canadian SLID micro data has been employed by several researchers to analyze particular aspects of the higher education decisions of youth. Frenette (2002, 2003) highlighted the strong impact of distance from the family home to the closest university and community college in determining attendance. Knighton and Mirza (2002) analyzed the simultaneous impacts of parental education and parental income on post-secondary education attendance. Coelli (2004a) employed the SLID to test whether tuition increases have impacted inequality of post-secondary education attendance in Canada. The results pointed to a marked negative impact of tuition increases on the education attendance of youth from low income families but not on youth from more advantaged backgrounds. None of these studies analyzed the impact of shocks to parental income on education attendance.

3 Model of Post-Secondary Education Attendance Decisions

The following economic model of education choice is described in order to motivate my empirical work. In line with standard human capital theory, youth are assumed to make an economically rational decision on whether to undertake further study by weighing expected benefits against costs. Expected benefits of higher education include higher salaries, lower unemployment rates, more interesting work, higher occupational prestige, and perhaps utility directly from studying. Costs include direct outlays such as tuition, books, supplies, and potentially the higher costs for travelling and living away from home. A major indirect cost is the income forgone while studying. Parents often assist their children in their education investments by providing financial support for direct education expenses and living costs.

A major potential constraint on youth attaining their individually optimal level of education is the incompleteness of loan markets for funding education investments. Private lenders are generally unwilling to lend to youth to finance education, as human capital cannot be repossessed by lenders if default occurs. Returns on educational investments are also uncertain, particularly as they depend on the effort of individuals both during study and during their working lives. Governments and even individual education institutions often provide student loans (or loan guarantees) and some non-repayable grants to students from low income households to minimize this loan market incompleteness.

3.1 The Youth's Attendance Decision

A partial equilibrium discrete-choice model of the post-secondary education (PSE) attendance decision is considered. This model closely follows Keane (2002). For more details of derivations of the model, see Coelli (2004b). A model with no borrowing constraints will be discussed first, with constraints added afterwards. The features of the model are as follows.

(a) Agents live for an infinite number of discrete time periods.

(b) Agents have per period preferences over consumption c and leisure l, represented by $u(c, l)$, concave in both arguments.

(c) Agents are endowed with L units of time each period, so $0 \leq l \leq L$.

(d) In period 1, agents decide whether or not to attend PSE. Tuition costs are τ, while studying requires s units of time. Agents receive direct utility from attendance of ϕ.

(e) In period 1, agents can choose to work any feasible $h \geq 0$ units of time at wage rate w_1. They also receive a transfer payment y_1 from parents[5].

[5]These transfers will be a function of parental wealth, number of siblings, etcetera.

(f) In every other period, agents inelastically supply one unit of time to work. The discount factor on future periods is $\beta = 1/(1+\rho)$. If the agent attended PSE in period 1, they earn wage $w_2 + \pi$ each period. If not, they earn w_2.

(g) Agents can choose to borrow any amount b in period 1. From period 2 on, they make fixed annuity payments of rb on the loan (b can be negative).

Lifetime utility of an agent who attends PSE is:

$$
\begin{aligned}
V_s &= \max_{\{h,b\}} u(y_1 + w_1 h + b - \tau, L - h - s) + \phi + \sum_{i=1}^{\infty} \beta^i u(w_2 + \pi - rb, L - 1) \\
&= \max_{\{h,b\}} u(y_1 + w_1 h + b - \tau, L - h - s) + \phi + \rho^{-1} u(w_2 + \pi - rb, L - 1) \qquad (1)
\end{aligned}
$$

Thus our infinitely lived agent model reduces to a two period model, simplifying the analysis considerably. Lifetime utility for an agent who chooses not to attend PSE is:

$$
V_o = \max_{\{h,b\}} u(y_1 + w_1 h + b, L - h) + \rho^{-1} u(w_2 - rb, L - 1) \qquad (2)
$$

These two maximization problems can each be solved for optimal work hours h and lending b[6], subject to $0 \leq l \leq L$. Assuming an interior solution for both h_s and h_o, the point of indifference between attending and not attending ($V_s = V_o$) is used to construct an approximate decision rule for PSE attendance[7]. The agent chooses to attend PSE if:

$$
\frac{\pi}{r} + \frac{\phi}{u_{c1o}} \geqslant \tau + w_1 s \qquad (3)
$$

The term u_{c1o} is the marginal utility of consumption in period 1, evaluated at the consumption level given non-attendance. Equation (3) highlights the trade-off between the benefits of higher education (wage premium π and direct utility ϕ) and the costs of tuition and income

[6] Optimal levels for these two decisions will not necessarily be the same for attenders and non-attenders.

[7] Keane (2002) generated this approximate decision rule employing a first order Taylor series approximation around the point of indifference.

foregone. The direct utility from PSE attendance ϕ is appropriately weighted by the marginal value of an extra dollar of consumption. The expected wage premium π and the utility of attendance ϕ can be treated as unobserved random variables. Such treatment generates a random utility model. Some agents may have very large dis-utility from attendance, if the effort required to complete studies is considerable. These agents may choose not to attend even when the average monetary payoff is expected to be large.

In this model with no borrowing constraints, the only role for parental transfers in the attendance decision is via the direct utility from attendance. Raising y_1 lowers u_{c1o} given decreasing marginal utility, raising the relative benefits of attendance[8]. Note that parental transfers here are not contingent upon the youth choosing to undertake further study. Contingent transfers will be discussed below.

Now consider the case where there are borrowing constraints in period 1. Agents cannot borrow in period 1 unless they choose to study. There is also a limit on borrowing given attendance of some fraction θ of the costs of studying (tuition level τ plus wages foregone $w_1 s$). Consider the case where the constraint binds[9], and all students borrow $\theta\tau$. Also, assume non-students are constrained to borrow nothing. The borrowing constraint for non-students will be binding if:

$$u_{c1o} > \frac{r}{\rho} u_{c2o} \tag{4}$$

Here, u_{c2o} refers to the marginal utility of consumption in all periods after period 1. Solving for optimal h_s and h_o, and again working from the point of indifference $V_s = V_o$, the approximate decision rule is now:

$$\frac{\pi}{r} \left[\frac{r}{\rho}\frac{u_{c2o}}{u_{c1o}}\right] + \frac{\phi}{u_{c1o}} \geqslant \theta(\tau + w_1 s) \left[\frac{r}{\rho}\frac{u_{c2}}{u_{c1}}\right] + (1-\theta)(\tau + w_1 s) \tag{5}$$

[8]If the agent has dis-utility from university attendance ($\phi < 0$), higher parental transfers will result in a lower probability of attendance. Thus extra income assists the agent in avoiding this dis-utility.

[9]If the constraint does not bind, the problem collapses to the case above.

If the borrowing constraint is binding, the term in the square brackets is necessarily less than one. Taking the simplest case where direct utility from attendance ϕ is zero, the presence of borrowing constraints makes it less likely that agents will choose to attend. The left hand side of the inequality in equation (5) is reduced more than the right hand side[10]. Increasing parental transfers y_1 will increase the term in square brackets towards unity, mitigating the borrowing constraint and making attendance more likely.

If parents choose to make a transfer y_s contingent upon their child attending PSE, it directly lowers the cost of attendance, just like a tuition subsidy or a government grant. The decision rule is altered as follows.

$$\frac{\pi}{r}\ \left[\frac{r}{\rho}\frac{u_{c2o}}{u_{c1o}}\right] + \frac{\phi}{u_{c1o}}\ \geqslant\ \theta(\tau + w_1 s)\ \left[\frac{r}{\rho}\frac{u_{c2}}{u_{c1}}\right] + (1-\theta)(\tau + w_1 s) - y_s \tag{6}$$

3.2 The Parental Transfer Decision

I now extend the Keane (2002) framework to analyze the parental transfer decision. If parents obtain some discrete increase in their own utility if their children attend PSE, contingent transfers will be rational. Parents may pay their children's tuition, but not give the same amount of money to a child who chooses to work instead. High income parents are able to absorb education costs while still benefitting from children attending. Parents with less income or who suffer negative income shocks may not be able to fund their children's studies without too large a reduction in their own consumption. To illustrate the parental decision on transfers to children, I begin by defining the following indicator function.

$$1[s_i|y_{sit}] = \begin{cases} 1, & \text{if child attends PSE} \\ 0, & \text{if not attend} \end{cases}$$

PSE attendance is a function of the contingent transfer y_{sit}, where the transfer occurs to child i in time period t, the time period the child attends. Parents will optimally make transfers

[10] If all PSE costs $(\tau + w_1 s)$ could be borrowed, attendance may be more likely if ϕ is positive.

just large enough to induce a child to attend. Parents make no transfers to children who do not attend ($y_{sit} = 0$). There are no purely altruistic non-contingent transfers here for simplicity, but including them does not alter the model's predictions. Parents are assumed to live for T periods, and to have I children[11]. The maximization problem of the parents can be written as follows, assuming parents can borrow and lend freely at interest rate r.

$$V_p = \max_{\{c_{pt}, y_{sit}\}_{t=1,i=1}^{T,I}} \sum_{t=1}^{T} \beta^t u\left(c_{pt}\right) + \varepsilon \sum_{i=1}^{I} 1[s_i | y_{sit}] \tag{7}$$

Subject to:

$$\sum_{t=1}^{T} \left(Y_{pt} - \sum_{i=1}^{I} y_{sit}\right) / (1+r)^t \geq \sum_{t=1}^{T} c_{pt} / (1+r)^t \tag{8}$$

The variable Y_{pt} denotes parental income in period t, and is assumed to be exogenous. It can include labour income, government transfers, gifts, inheritances, in addition to income from assets, including liquidation of such assets. The parameter ε denotes the discrete increase in parental utility from a child attending PSE. If the rate of time preference β equals $1/(1+r)$, parents will smooth own consumption to be an equal amount $\overline{c}_p$ each period.

$$\overline{c}_p = r\left[1 - \left(\frac{1}{1+r}\right)^T\right]^{-1} \sum_{t=1}^{T} \left(Y_{pt} - \sum_{i=1}^{I} y_{sit}\right) \tag{9}$$

Parents optimally make positive contingent transfers if the reduction in utility from reduced own consumption is less than ε. If there is only one child in the family ($I = 1$), the problem is straightforward. An approximate decision rule is for parents to make contingent transfers if the following condition holds.

$$\varepsilon \geq u'(\overline{c}_p) \left(\frac{1}{1+r}\right)^t y_{s1t} \tag{10}$$

Parents with more income, and thus higher $\overline{c}_p$, are more likely to make such contingent transfers, given concave utility in own consumption. If there is more than one child, parents may no longer fund all their children through PSE. The probability of attendance, given

[11]The number of children is assumed exogenous here, as modelling fertility is beyond the scope of this analysis. The number of time periods T can also be infinite as for youth.

parental income, may be lower for each child in a larger family, thus family size may impact education attainment[12].

If parents suffer some income shock, its impact on the PSE attendance of their children will depend on whether the shock is expected to be temporary or persistent. Temporary shocks may be overcome by borrowing or running down savings. If parents cannot borrow freely over time periods, and they have not built up savings prior to the shock, then even shocks which are expected to be temporary may significantly impact the education attendance of their children. The results of this analysis suggest that it is parental income shocks that are persistent, such as those caused by job loss, which have more considerable negative impacts on their children's education attendance.

4 The Data and the Canadian Education System

4.1 The SLID Data

The Survey of Labour and Income Dynamics (SLID) is a household-level longitudinal survey of Canadians. Approximately 15,000 Canadian households are chosen for inclusion in the Survey every three years. Once a household is chosen for inclusion in the survey, all members of the household at that time are interviewed annually for six years, even if they leave the original household at any stage during the period[13]. Interviewing survey respondents annually irrespective of where they live is especially important for this study, as youth completing high school may leave the parental home to either work or study. This analysis requires information on the

[12] Which children attend PSE in a family may depend upon the individual preferences or abilities of children for education. Parents may also choose to send the eldest first, and keep sending children until it is no longer optimal to do so. Parents can brag earlier and longer when the elder children attend, so birth order may also determine attendance.

[13] Individuals who enter a household where a SLID longitudinal respondent resides during this six year period are also interviewed, but are not longitudinal respondents and are not included in this analysis.

education attendance decisions of youth at the end and following high school. Youth who leave the household are followed to their new residence and surveyed in the same manner as youth who remain in the parental home. The second major advantage of the SLID micro data for this study is the availability of information on the income and labour market outcomes of parents for each year. I employ this information to construct indicators of major parental income shocks over the period when the youth are deciding upon their higher education attendance.

Having both measures of parental shocks and year to year education enrollment information on youth is a particular advantage that the SLID micro data has over the major representative micro data sets employed to analyze the education decisions of youth in the U.S. The Panel Study of Income and Dynamics (PSID) does not have detailed year to year education enrolment information for young adults. The education questions are not very detailed for household members who are not the household head. The National Longitudinal Study of Youth (NLSY) does not collect annual parental income and labour market outcome information for all youth of school-leaving age. In particular, detailed parental income and labour market information is not collected for youth who leave the parental home.

The first longitudinal panel of the SLID runs from 1993 to 1998. The second panel runs from 1996 to 2001. Outcomes for youth from panels one and two are analyzed here[14]. In this analysis, youth will first be observed at age 16, when they are still in high school, prior to making their own decisions on education attendance. At this age, the vast majority of youth still live with at least one parent (around 98%). Accurate parental information is thus obtained for almost all youth. The education decisions of these youth will then be observed from age 16 until a maximum age of 20. By age 19 or 20, most Canadian youth have had the opportunity to obtain the education pre-requisites for university and college acceptance. The majority of

[14] A third panel was begun in 1999. Access to the full SLID data was made possible via the British Columbia Interuniversity Research Data Centre (BCIRDC) at the University of British Columbia.

individuals who attend university and community college begin their attendance by this age. The rate of initial entry into higher education studies falls considerably after this age.

4.2 The Canadian Post-Secondary Education System

The vast majority of universities and community colleges in Canada are publicly owned. Provincial governments provide the majority of funding for these institutions, particularly for educational operations. If desired, they can also exercise control over tuition and enrollment levels at institutions. The Canadian Federal government also provides funding to these institutions, but mostly for research. Universities in Canada are degree granting institutions, with most bachelors degrees requiring a minimum of four years of study. Entrance to university requires twelve years of elementary and secondary school study in most provinces[15]. Community colleges in Canada do not generally grant degrees, and high school graduation is not always required for entry. These institutions grant certificates and diplomas for studies which take from one to three years to complete.

Universities and community colleges in several Canadian provinces increased tuition markedly over the 1990's, particularly in Ontario, Alberta and Nova Scotia. Tuition fees were deregulated in several provinces, while Quebec and British Columbia instituted tuition freezes over this period[16]. Movements in average real tuition levels at universities and community colleges in Canada are illustrated in Figure One. Average tuition levels in many provinces are approaching average levels at public four year colleges in the US. Provincial government funding of higher education remained stagnant or fell in real terms over the 1990s, as did government funding of most expenditure categories. Aggregate enrollment at PSE institutions in Canada

[15]Quebec and Ontario have alternative requirements, and are discussed further below when the data is described.

[16]British Columbia lifted the freeze in 2002, while in Quebec, tuition has still not increased since the mid-1990s.

stagnated over the 1990s, but it did not fall (see Figure Two). Overall education attainment of Canadian youth does not appear to have been negatively affected by the tuition increases.

The main sources of loans and non-repayable grants for post-secondary education students in Canada are the Canadian Student Loan Program (CSLP) and Québec's Aide financière aux études program. Eligibility for financial aid under both programs is based upon parental income, family size, place of residence and direct education costs (particularly tuition). These loans are subsidized by the government[17]. Only youth from less advantaged backgrounds can access loans from these programs. In the application process, potential student borrowers must provide information on their parent's income from the previous year's tax return. The more parents earn, the amount that youth can borrow from these programs is reduced on an increasing percentage basis. Between 40% and 50% of Canadian college and university bachelors graduates have student loan debts at the end of their studies. These student loan programs are similar in nature to the Stafford Loan, the largest student loan program in the U.S. Finnie (2001) provides more details of Canadian student loans[18]. Many universities also provide scholarships and bursaries directly to students. This type of support has increased in the 1990s as tuition fees have increased.

4.3 Main Measures Employed in the Analysis

Post-secondary education (PSE) attendance is identified as follows.

[17] Subsidy takes the form of no interest being payable on the loans until the student leaves full-time study. There are also provisions in place for loans or loan interest to be written off in the case of severe financial hardship.

[18] There was a shift towards more student financial aid being provided in the form of loans rather than non-repayable grants over the 1990s in several Canadian provinces. The CSLP program has moved in the opposite direction to some degree, with scholarships being provided to students who are both in need and do well in the first year of university study under the Canadian Millennium Scholarship Fund program. This program started disbursing funds to students in 2000, right at the end of my data period. Quebec remains as the one province which provides significant funding to PSE students via non-repayable grants, but these grants are made to the most disadvantaged youth only.

- Attended university - if the youth attended university for any length of time and at any age from 17 up to and including the second year after normal completion of university entrance requirements.

- Attended other PSE only - if youth ever attended a community college, *CEGEP*[19], business school, trade or vocational school at any age from 17 up to and including the second year after normal completion of university entrance requirements, but never attended university over the same period.

- Not attend PSE - if neither of the above two items are true.

The second year after normal completion of university entrance requirements is defined as age 20 for youth from Quebec and Ontario, and age 19 for youth from any one of the remaining eight provinces of Canada. The difference reflects the extra year of study in Ontario (grade 13) required for acceptance by many universities in that province[20]. It also reflects the Quebec higher education system, where youth must attend a *CEGEP* for two years after grade 11 in order to attend university. To be included in this analysis, each youth must be observed annually from age 16 up to 19 or 20, depending on the province of residence at age 16. Youth from Quebec and Ontario aged 15 or 16 at the start of each panel and youth aged 14, 15 or 16 in the remaining provinces are included. The final sample employed covers 1,335 observations after exclusion of individuals for missing data. See Appendix A for details of how the final sample was obtained.

Attendance rates for the full sample are presented in the first column of Table 1. Overall, 30% attended university, 35% attended other PSE only (not university), while the remaining 35% did not attend any PSE within this period. The next three columns of this table present

[19] The Quebec college system, collège d'enseignement général et professionel.

[20] This requirement was dropped in 2003, but this is after the time period being studied here, which is 1993 to 2001.

attendance rates for youth from low, middle and high parental income backgrounds. See Appendix B for details of how these parental income quantiles were constructed. Note the strong relationship between parental income and education attendance. Youth from low income backgrounds are much less likely to attend university. One of the main objectives of this study is to ascertain whether this strong relationship is causal.

Parental income is measured by the sum of the total real after tax annual income of the parents the child lives with at age 16. The vast majority of income measures in the SLID survey are taken from tax records, so they should have a high degree of accuracy[21]. Changes in parental income are calculated for three annual changes and for the change over the entire three year period from when the youth was aged 16 to when the youth was aged 19. Table 3 provides percentiles of the distribution of these annual parental income change measures. Large changes in income can be observed for significant proportions of the sample, both in the annual changes and in the change over the entire three year period. Over ten percent of parents in the sample suffer from a reduction in real (2001 Canadian) income of fourteen thousand dollars or more over the three year period from when the youth is aged 16 to when the youth is aged 19. Year to year reductions of ten thousand dollars or more are also suffered by 10% of the population.

These measures of changes in income will capture both temporary and more persistent income shocks. Jacobson, LaLonde and Sullivan (1983) and others have illustrated clearly the persistent effect that exogenous job loss can have on income over many years. I employ parental job loss resulting from exogenous factors to indicate persistent negative income shocks in this study. Exogenous job losses were identified by the parents' main job ending due to: (a) layoff/business slowdown (not caused by seasonal conditions), (b) company going out

[21]Respondents to the SLID are given the choice of making a self-report of income during a second annual interview in May of each year or allowing Statistics Canada to access their income tax records.

of business, or (c) dismissal by employer.

I identify job loss for both the main income earner and the spouse in the youth's family. Main income earner status was self-reported by the parents in the SLID survey[22]. Table 2 provides summary statistics for these job loss indicators. Significant proportions of parents suffered from job losses each year. The final column includes measures denoting the average number of youth who suffered from parental job loss at any age from 16 to 18. In the analysis to follow, I find that it is main income earner job loss that is particularly important in having both persistent negative impacts on parental income and on the education attendance of youth.

Job losses are correlated over time for these parents. Many parents suffer from job losses in more than one year when their child is aged 16, 17 and 18. Of the eleven percent of main income earners who suffered from at least one loss over these years, nearly two thirds suffered from more than one such loss. This may reflect the type of work the parents undertake. Some occupation types may be more prone to jobs which last for a short period of time, and where finding another similar job is not difficult. Controlling for parents who suffer multiple job losses will be important in the analysis to be performed in Section 6 below.

5 Post-Secondary Education Attendance Model Estimation

If parental income shocks are correlated with other parental characteristics that impact the education attendance of youth, controlling for these characteristics is important when identifying causal impacts. As an example of what may be of concern here, income shocks were more common in families with less educated parents. As parental education is highly correlated with education attendance, controlling for differences in parental education levels is important

[22] For two parent families, 77% of main income earners were male, and 94% of main income earners actually had the higher level of income of the two parents in the family. For lone parent families, 74% of lone parents were female in the sample. Lone parent families composed 15% of the final sample.

when attempting to identify causal impacts.

The objective in this section is to uncover causal impacts of parental income in a transparent reduced-form framework. I decompose parental income shocks into persistent and temporary components using job loss. The impact of parental job loss on attendance is also broken down by several important characteristics of parents, such as education levels and age. In the next section, I estimate a full year-to-year grade transition model. Using those estimates, the impact of permanent income shocks (indicated by job loss) on immediate high school dropout behaviour as well as on eventual PSE attendance outcomes of youth are identified.

5.1 The Estimated Model

I employ the model outlined in Section 3 as a basis for constructing post-secondary education (PSE) attendance decision rules for estimation using standard limited dependent variable techniques. The multi-nomial logit technique was employed to estimate the attendance decisions of youth among the following three choices: (a) attend university, (b) attend other PSE (non-university) only, and (c) not attend PSE at all. The two-option model of Section 3 (attend PSE or not) can easily be expanded to this three-option choice. Youth will choose the option that maximizes their net expected lifetime utility. The multi-nomial logit technique places no ordering on the three choices, unlike the ordered probit technique employed by Hilmer (1998).

A list of the covariates included in estimation is provided in Table 4, along with sample summary statistics. These covariates include measures of parental education, average real parental income (a three section spline was employed), number of dependent children, gender, visible minority status, immigrant status of parents, French mother tongue, city and rural indicators, and indicators of distance to the closest universities and colleges. The estimated models also include direct measures of tuition fees and university provided financial aid[23]. A

[23]As discussed in Section 4 above, the main sources of loans and bursaries for undergraduate students in Canada

description of all the variables is provided in Appendix B.

The estimated equations include gender-specific time trends[24]. Time trends will account for any changes in the average expected PSE wage premium π over time[25]. Direct utility from education attendance ϕ will be a function of the individual ability and preferences of youth. This direct utility is proxied by many of the individual and parental characteristics listed in table 4. Note that these characteristics may also impact any individual specific component of wage premium expectations. The opportunity cost of time while studying $w_1 s$ is proxied by provincial youth unemployment rates, which reflect the probability of obtaining employment if youth do not attend PSE[26]. Empirical evidence suggests that school attendance is counter-cyclical in Canada (see Beaudry, Lemieux and Parent (2001)). Provincial region dummies are also included in the estimated equations to control for differences in education systems across Canada[27]. By including these regional indicators, the data variation employed for identifying impacts of provincial measures such as tuition fees is within province variation over time. This model specification relies on there being an integrated labour market in Canada, with a common trend in the PSE wage premium across provinces.

I include parental income shock measures in these estimated education attendance models. These shock measures will capture the impact of unexpected reductions in parental income on

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are the Canadian Student Loan Program (CSLP) and Québec's Aide financière aux études program. Eligibility for financial aid under both programs is based upon parental income, family size, place of residence and direct education costs (particularly tuition). Historic eligibility rules were employed to construct financial aid eligibility indicators for each individual in the sample. These measures were not included in the final analysis due to their very close relationship with the individual characteristics already included in the estimated equations.

[24]Estimates including gender-specific time dummies in place of linear trends did not change the results to any extent.

[25]Estimates of contemporaneous average wage premiums were constructed using SLID data, but showed no strong trend over the period under analysis. University premiums were higher for women than men, while other PSE (community college, trades) premiums were higher for men.

[26]Measures of alternative wages such as the minimum wage had no significant impact on attendance probabilities.

[27]The model was also estimated including the full set of provincial indicators, but the restriction of including four regional indicators only was easily accepted by the data.

attendance. If these shocks are expected to be persistent, or if parents cannot access funds to smooth over temporary income shocks, reductions in transfers to children may result, which in turn may lower university and other PSE attendance probabilities.

5.2 PSE Attendance Model Results

Results of multi-nomial logit estimations of the three option PSE attendance choice of youth are presented in Tables 5 and 6. The marginal effects presented in these tables are the impact of each variable on the probability of attending university and other PSE respectively[28]. The marginal effects for the base case of not attending any PSE are not reported for brevity. Standard errors on these marginal effects, reported in parentheses, were corrected for potential heteroscedasticity using the White procedure, and for clustering by province and year[29].

The multinomial logit model is based on the assumption of independence from irrelevant alternatives (IIA). This assumption implies that adding another alternative to the model does not affect the relative odds between two alternatives already included in the model. This appears to be a strong restriction here, as we may think that adding the alternative of other PSE will change the odds of choosing between university and no post-secondary study. A Hausman and McFadden (1984) test of the IIA assumption, however, could not be rejected. This test is based on separate binary logit estimation of university and other PSE attendance versus non-attendance, and tests if the coefficient estimates from the separate regressions are different to ones from the full multinomial logit estimation. No significant difference in the estimated coefficients could be observed.

[28]All marginal effects were calculated with all indicator variables set to zero and continuous variables set to the values faced by an individual with all indicator variables set to zero (e.g. a male from Ontario turning 16 in 1995). The time trend was set to a value of three (third year in sample, which is 1997), and the children in the family variable was set to three also.

[29]Adjusting standard errors for potential clustering is important here as several of the covariates employed, such as tuition, are common to all observations in a province-year cell. Probability weights for longitudinal respondents provided in the SLID were employed during estimation.

The results for three versions of the attendance model are presented in Tables 5 and 6. Each version includes one measure of parental income shock. In column one, the annual parental income change (in thousands of real dollars) from when the youth is age 18 to age 19 is included. In column two, the change over the whole period from age 16 to age 19 is included. In column 3 an indicator of any job loss of the main income earner when the youth is aged 16, 17 or 18 is included. The impact of the individual and parental characteristics on attendance are interesting in their own right. These characteristics are much more significant in predicting university attendance than they are in predicting other PSE attendance. The estimated impacts are also little changed by which parental income shock measure is included in the estimates as we look across the columns in Tables 5 and 6.

Looking first at the marginal effects for university attendance (Table 5), females are much more likely to attend university than males. This gap also appears to be increasing over the period, indicated by a positive female time trend (not reported) [30]. Youth of aboriginal descent are much less likely to attend university, while visible minorities and youth with an immigrant parent are much more likely. Having one more child in the family has a small and statistically insignificant negative impact on university attendance. Youth from lone parent families are much less likely to attend university, even controlling for differences in parental income. This negative impact of eleven percentage points is larger than that found by Ver Ploeg (2002)[31], but is similar to that found by other researchers using US data.

Parental education and income levels are strongly positively related to the probability of attending university. Parental education has a larger impact than parental income, but both

[30]Note that the marginal effect for the female indicator works through both the estimated coefficient on the indicator itself and the female-specific time trend. The female time trend was set to zero for calculating all marginal effects except for the marginal effect of the female-specific trend itself. In this case the female trend was set at the value of three, the same value set for the overall time trend.

[31]Ver Ploeg found much larger income effects than I have, but her use of predicted income for many individuals may be driving her results.

measures are closely related. This illustrates clearly that university attendance in Canada is a long way from equality, a result also indicated in Table 1. Youth from more advantaged backgrounds are much more likely to attend.

Changes in community college tuition have a large and statistically significant negative impact on university attendance, while university tuition has a smaller negative impact. These marginal effects are the impact of a $500 increase in fees in 2000/01 Canadian dollars on attendance[32]. This implies a negative cross-price effect (from community college tuition) on university attendance. This may reflect a negative impact on university attendance via lower community college attendance, if community college transfer is chosen as an alternative pathway to university. It may also reflect the close correlation in the two tuition measures within provinces. Many provinces increased tuition at both universities and community colleges at the same time and by similar dollar amounts. The correlation between the two measures at the provincial level is a considerable 0.7 over the period under analysis.

Living further than eighty kilometres from the nearest university had a statistically insignificant negative impact on university attendance[33]. There is an insignificant positive impact of living further than 40 kilometres from the nearest college on university attendance. This may reflect the placement of colleges in areas of historically low PSE attendance in order to encourage increased attendance[34]. The regional indicators (not reported) highlighted much higher rates of university attendance in Atlantic Canada and Ontario than in the rest of Canada.

The effects of the set of characteristics on attendance at other PSE institutions (primarily community college) are much less significant than their effects on university attendance. Youth

[32]This is approximately $400 in U.S. currency at 2004 exchange rates and prices.

[33]Frenette (2003) found significant negative impacts in more parsimonious models.

[34]This variable may thus be proxying characteristics of the neighbourhood of residence on attendance probabilities. I have analyzed the impact of neighbourhood characteristics on attendance in related work (see Coelli (2004a)).

of aboriginal descent are less likely to attend other PSE, as they were in attending university, but the effect is statistically insignificant. Parental education and income levels have economically small impacts. This illustrates that there is little inequality in other PSE attendance rates overall in Canada, unlike at the university level.

The signs of the impacts of tuition fee levels on other PSE are economically appropriate. Higher community college tuition lowers the probability of attending other PSE, providing evidence of a negative own price effect. Increases in university tuition raises the probability of attending other PSE, highlighting a positive cross-price elasticity. Both these impacts are economically small and not statistically different from zero[35].

The estimated impacts of the parental income shock measures on university and other PSE attendance are gathered in Table 7 for ease of comparison. The marginal effects for three shock measures are taken directly from the bottom rows of Tables 5 and 6. The final column in the table is the estimated impact of the shocks on not attending any PSE in this period. Marginal effects for changes in income in any one year or over the entire three year period are presented in the top panel of Table 7. These marginal effects were calculated for a ten thousand dollar reduction in annual income[36]. Even for such a large income reduction, very little impact on PSE attendance is observed. There is a statistically significant decline in university attendance for a reduction in income over the entire three year period, but it only lowers the probability of university attendance by 1.4 percentage points. To understand the size of these impacts, recall that 30% of youth attend university and 35% attend other PSE in this sample overall.

Job loss shocks to the main income earner in the family, however, lead to a large and statistically significant ten percentage point decline in the probability of university attendance.

[35]There was also a very large impact of residing in Quebec on other PSE attendance, reflecting the high rates of attendance at *CEGEP*s in that province.

[36]Models were estimated including percentage changes in income rather than dollar changes. Results suggested that dollar changes were more significant predictors of attendance.

This is evidence of a particularly alarming impact of labour market dislocation. Spousal job loss shocks, in contrast, have no significant impact on PSE attendance[37]. Main income earner job loss alone impacts PSE education attendance here.

5.3 Permanent and Temporary Income Shocks

The insignificance of the impact of income changes on university attendance contrasted with large impacts of main income earner job loss deserves further scrutiny. Not all observed changes in parental income may be shocks, and many changes may only be temporary in nature. They may reflect large increases in income in the previous year, perhaps due to the realization of a capital gain. Exogenous job loss, on the other hand, may reflect a more persistent and unexpected shock to parental income, which have a more marked impact on the education attendance of youth. To uncover the impact of persistent and temporary parental income shocks on PSE attendance, I decompose changes in parental income into a permanent component due to job loss and a temporary component. I then include these permanent and temporary parental income changes in the multinomial model of PSE attendance.

To begin, I estimate an ordinary least squares regression of parental income changes over the entire three year period (age 16 to 19, denoted $PIC3yr$) on main income earner job loss at age 16 (denoted $MJL16$). Standard errors are in parentheses.

$$\begin{array}{rcccl} PIC3yr_i & = & 3.01 & - & 18.13 \times MJL16_i + resid_i \\ & & (.63) & & (2.12) \end{array}$$

Parental income falls by a highly significant eighteen thousand dollars (2001 Canadian) on average over the three years following job loss[38]. This fall is the permanent component

[37] New work limitations to the family's main income earner and spousal separation also had ten percentage point negative impacts on university attendance.

[38] Main income earner income fell by sixteen thousand dollars itself due to the job loss. Spousal income did not offset the main income earner reduction at all, and even exacerbated it.

of the income change. The temporary component is the residual ($resid_i$) from this regression. These large income falls following exogenous job loss are in line with the findings of Jacobson, LaLonde and Sullivan (1983). In contrast, spousal job loss only led to a two thousand dollar reduction in annual spousal income over the three year period following the loss.

The multinomial logit model estimates of the marginal effects of these permanent and temporary measures of parental income shocks are presented in Table 8[39]. A reduction in permanent income of ten thousand dollars results in a 6.6 percentage point reduction in university attendance. In contrast, temporary income falls of the same magnitude have a small and statistically insignificant negative impact on PSE attendance. This suggests that temporary income shocks can be smoothed by families with little impact on the education attendance of their children. On the other hand, parental income shocks that are expected to be persistent have marked effects.

5.4 Breakdown of Impacts by Parental Characteristics

I break down the impact of main income earner job loss on attendance by various important parental characteristics in Table 9. These breakdowns were constructed by including interactions of the shock measures with the parental characteristics in the estimated models. Looking first at the top panel, the negative impact of job loss on university attendance is confined to parents with a high school education or less. More educated workers may find it easier to obtain another well-paying job. Job loss resulted in larger declines in parental income for less educated parents over the three years following the loss. The income fall for parents with high school or less was $20,000, while for parents with a completed post-secondary education it

[39]Standard errors were adjusted for the first stage OLS estimation (generated regressors) using the adjustment technique for two-stage M-estimators described by Wooldridge (2002, pp. 361-362).

was $13,000[40].

Older parents may be able to smooth the effects of negative income shocks more easily than younger parents. They may have been able to save more over a longer working life, providing more access to resources for their children. Younger parents may still be committed to large housing mortgage repayments. There was no statistically significant difference in the impact of job loss by parental age, however. Parental age itself is significantly positively related to university attendance. The top row of the bottom panel of Table 9 illustrates that a five year increase in parental age raises the probability of university attendance by 0.6 percentage points. The interaction term between job loss and parental age in the bottom row is not statistically different from zero, however[41].

I analyzed several additional breakdowns of the impact of parental income shocks on education attendance. The impact of job loss on attendance did not depend on the length of time parents remained unemployed following job loss. The strength of job loss impacts was not related to university and college tuition levels either. The impact of income changes on attendance did not depend on whether the parents were self-employed or not. There was also no evidence that positive and negative income changes had different impacts on attendance. The estimation results for these breakdowns are available in Coelli (2004b).

6 Grade Transition Model of Education Attendance

In this section, I estimate a model of the full set of annual education attendance outcomes of youth from age 16 to age 19 or 20. This model is employed to identify the immediate and lagged impacts of permanent parental income shocks, indicated by job loss, on those education

[40]Shea (2000) also found a small causal negative impact of average parental income levels, instrumented by job loss, on youth's completed years of schooling for low educated fathers.

[41]The age of the main income earner was employed here.

outcomes. Due to the limited length of each panel in the SLID, the two stage technique decomposing income changes into permanent and transitory components could not be conducted here for job losses at age 17 and 18. Job loss indicators for the family's main income earner alone are included in the model to identify persistent parental income shocks. Using this model, I am also able to construct a specific test of the exogeneity of these job loss indicators to further ensure a causal impact is being uncovered. This test should allay any remaining concerns that job loss itself reflects unobserved characteristics of parents which may also impact their children's education attendance.

6.1 Grade Transition Details

Education attendance is a sequential process. To complete high school, students must first complete grade 10, grade 11, etc. To attend university, youths must first complete high school or an equivalent. I explicitly model annual education outcomes here while imposing these sequential constraints on each individual's attendance alternatives. An illustrative diagram of a subset of the education transitions modelled is provided in Figure Three.

Youth are first observed at age 16. The vast majority of youth are still in high school at this age, and have completed either nine or ten years of elementary and high school. A year of high school is generally completed in the middle of a calendar year, with the next grade or level of education (college or university) beginning in September.

The first transition observed is from age 16 to age 17. Youth in grade ten at age 16 can stay in school and complete grade 11 during the calendar year they turn 17, they can attend other post-secondary education (PSE) such as trade school[42], or they can drop out of education altogether. Youth are legally able to leave school after they turn 16 in Canada[43]. Youth in grade

[42]Attending other post-secondary education at this age was not common except in Quebec.

[43]Youth who do not attend school at all or for less than 4 months during the calendar year are denoted dropouts.

nine at age 16 can also drop out, attend other PSE or progress to grade ten at age 17.

The second transition observed is from age 17 to age 18. Youth who complete grade eleven during the calendar year they turn 17 can complete grade twelve in the middle of the calendar year they turn 18 and then progress to university. They can also go on to other PSE, just complete high school, or drop out. Youth must generally complete twelve years of high school to attend university in Canada. There are two exceptions: Quebec and Ontario. These cases were discussed in Section 4, and are modelled explicitly in this grade transition model. For more details of the measurement of the transitions and the finer details of the transition model, see Appendix C. Youth in grade ten at age 17 can progress to grade eleven during this second transition, attend other PSE, or drop out. They cannot attend university yet. Youth who dropped out of school during the first transition can stay out, return to school, or in some cases attend other PSE. They cannot attend university yet either.

The third transition from age 18 to age 19 has similar transitions modelled, including transitions for youth who have completed twelve years of high school and for youth attending other PSE. Not all of these transitions are presented in Figure Three due to space limitations. Those youth who reported university attendance at age 18 are no longer modelled, as university attendance is defined as the highest attendance level obtainable. A fourth transition from age 19 to age 20 is modelled for youth from Ontario and Quebec only. This was undertaken to give youth from those provinces the extra year they generally require to obtain the pre-requisites for university entrance.

6.2 Econometric Model

The importance of controlling for unobserved heterogeneity was illustrated clearly by Cameron and Heckman (1998) when estimating these grade transition models. Characteristics such as innate academic ability impact the education outcomes of youth, but are generally unobservable to us as researchers. Ignoring the impact of these unobservables may lead to biased estimation of the impact of observable characteristics, such as parental income or parental income shocks, on education decisions. Selectivity bias that may be caused by the exclusion of such unobserved characteristics is controlled for using the random effects estimation technique proposed by Heckman and Singer (1984).

The econometric estimation strategy follows closely Cameron and Heckman (2001). Let a denote age, where $a \in \{\underline{a}, ..., \overline{a}\}$, with $\underline{a}$ being the initial age of 16 and $\overline{a}$ denoting the highest age observed (age 19 or 20). Schooling status at age a is denoted j_a, and this status will determine the available schooling choices at age $a+1$. Youth with schooling level j_a make a choice about their schooling level at age $a+1$ from choice set C_{a,j_a}. Let $D_{a,j_a,c} = 1$ if choice $c \in C_{a,j_a}$ is chosen by a youth of age a with schooling status j_a. Let $D_{a,j_a,c'} = 0$ otherwise, where $c' \neq c$.

Each education decision is the result of a rational decision made by the youth. The youth will calculate the expected utility $V_{a,j_a,c}$ from each available choice c, then choose the one which maximizes their expected utility. This utility calculation will include the option value of further education attendance in many cases. For example, continuing on in school versus dropping out will keep open the option of attending university. The utility of each choice will be approximated by a linear equation as follows.

$$V_{a,j_a,c} = Z^{'}_{a,j_a,c}\beta_{a,j_a,c} + \varepsilon_{a,j_a,c} \tag{11}$$

The vector $Z^{'}_{a,j_a,c}$ is a set of observable characteristics while $\varepsilon_{a,j_a,c}$ is unobservable. The unobservable is assumed to follow the following simple factor structure.

$$\varepsilon_{a,j_a,c} = \alpha_{a,j_a,c}\eta + \nu_{a,j_a,c} \tag{12}$$

Here η is a mean zero random variable with unit variance, and which is independent of $\nu_{a,j_a,c}$. Both η and $\nu_{a,j_a,c}$ are assumed independent across youth. The random variables $\nu_{a,j_a,c}$ are assumed to follow extreme value distributions, and are independent of all other $\nu_{a',j''_a,c'''}$. These assumptions produce an extension of the multinomial logit model. Conditioning on η yields the following, where the matrix Z_{a,j_a} denotes the set of $Z_{a,j_a,c}$.

$$\begin{aligned}\Pr(D_{a,j_a,c'} = 1|Z_{a,j_a}, \eta) &= \Pr(\arg\max_c V_{a,j_a,c} = c'|Z_{a,j_a}, \eta) \\ &= \frac{\exp(Z'_{a,j_a,c'}\beta_{a,j_a,c} + \alpha_{a,j_a,c'}\eta)}{\sum_{c\in C_{a,j_a}} \exp(Z'_{a,j_a,c}\beta_{a,j_a,c} + \alpha_{a,j_a,c}\eta)}\end{aligned} \tag{13}$$

The main consequence to note from the assumptions of this model is that any dependence between choices $D_{a,j_a,c}$ and $D_{a',j''_a,c'''}$ ($a \neq a'$) made by any individual youth, conditional on observables, arises from η, the youth specific effect. To account for this dependence, model estimation involves integrating out the η using an approximation of its distribution $F(\eta)$. The approximation employed is a discrete distribution with mass points. See Appendix C for details of the estimated likelihood function.

This estimation technique is a form of random effects estimation, and is based on the assumption that η is independent of the set of observable characteristics of youth (the $Z_{a,j_a,c}$ for all $a, j \in C_{a,j}$). The unobservable η may, however, be correlated with the included regressors in any one of the particular estimated transitions ($a > \underline{a}$), as these estimated transitions are dependent on the past attendance outcomes of an individual youth. If the unobservable reflects ability, for example, it may be negatively correlated with parental income for those still in school at ages 17 or 18. This will occur if having low parental income increases dropout behaviour, so only high ability youth from low income backgrounds remain in school.

The base case at the initial age of 16 is the determination of whether the youth has completed nine or ten years of high school. This will generally depend on whether or not the youth had to repeat a grade of school prior to age 16, or who started school a year later than normal. This will be a function of the youth's ability and motivation, parental inputs into their children's education, and perhaps quarter of birth. It is modelled by a linear in variables logit equation with the full set of individual, parental and environmental characteristics employed in the transition estimates, plus indicators of quarter of birth[44].

For each decision among a set of choices C_{a,j_a}, I must normalize one set of parameters $\beta_{a,j_a,c}$ in order to identify the remaining parameters for that decision. Denote the choice c_a^* as the normalization or base case. The parameters β_{a,j_a,c^*} and factor loading α_{a,j_a,c^*} were constrained to zero within each choice set. As a result of this normalization, the remaining estimated coefficients and factor loadings are defined relative to those for the base case. I set the base case to either the dropout or non-progression choice in each decision during estimation[45].

6.3 Estimation Preliminaries

Parameters governing the initial condition at age 16 and governing three or four annual education transitions (depending on province of residence) are estimated, with separate estimates for each possible beginning education state at each age. The number of possible transitions and the choice sets available both expand considerably as the youth ages. Several procedures were followed to minimize the number of parameters estimated.

To begin, there were a number of transitions where the number of observations undertaking a particular choice was too small to estimate all the slope coefficients. Choices with fewer than 15 observations were estimated with constants only. Choices with between 15 and 30 observations were estimated with a constant and two indicators of parental income quantile only. Factor loadings on the unobserved characteristic η were set to zero for these choices.

[44]Quarter of birth may impact years of school completed by a particular age if children turning six years old late in the year are not entered in school until the year they turn seven. This may occur due to parental choice or school district regulation.

[45]The decision of base case between these two states was made on the basis of the number of observations within each choice.

In addition, several hypotheses regarding the estimated slope coefficients were tested, and those that were not rejected by the data were imposed in final estimation. Separate constants were retained in each case. The restrictions imposed were as follows.

1. The slope coefficients on school dropout transitions were restricted across the last three transitions.

2. The slope coefficients on the grade nine and grade ten progression transitions in the first transition were restricted to be equal.

3. Grade eleven transition slope coefficients in the second and third transitions were restricted to be equal.

4. High school graduates transitions in the third and fourth transitions were also restricted to be equal.

The model was estimated including the set of individual and parental characteristics listed in Table 4[46]. The provincial level characteristics which change over time were entered at the appropriate level for that year. For example, the university and college tuition levels that were charged in the province of residence when a particular youth was 17 was included in the first transition (age 16 to age 17) for that youth.

Job loss indicators were included in transitions which occurred after the job loss occurred. The indicator of a parental job loss when the youth was aged 16 was included in the first transition for that youth. This indicator plus the indicator of a job loss when the youth was aged 17 were included in the second transition. These two plus the indicator of job loss at age 18 were included in the third transition. Shocks could impact the current transition and future

[46] A number of characteristics were dropped from estimation due to statistical insignificance and estimation problems: aboriginal descent, visible minority status, French speaking, city and rural indicators, and university over 40 kilometres away.

transitions of youth but not past transitions. In other words, shocks could not affect transitions which are undertaken before they themselves occur. This restriction on the inclusion of shocks in the model was tested in order to illustrate that these shock measures are truly exogenous. The results of these tests are discussed below.

I estimated each model both with and without controlling for unobserved heterogeneity. Unlike the results of Cameron and Heckman (2001), controlling for unobserved heterogeneity did not change the model estimates to any significant extent. Only two points of support were required to adequately capture the distribution of the unobservable η in the data. This low number is common in estimation of models such as this, including the work of Cameron and Heckman. The unobserved heterogeneity was estimated recursively, using the initial condition at age 16 to identify the probabilities on each of the mass points for η. The model simulations discussed below were constructed using model estimates which included the controls for unobserved heterogeneity.

6.4 Grade Transition Model Results

I employ the estimates of the full grade transition model to simulate the impact of parental job loss on the annual education outcomes of youth from age 17 to age 19 or 20 (depending on province of residence). These results are presented in Table 10[47]. These simulations depict a treatment on the treated effect. It measures the average impact of parental job loss on the education outcomes of those youth who suffered from the shock. Treatment effect construction involved simulating the estimated probability of each annual education outcome for each youth who suffered from parental job loss twice. First, the attendance probabilities are simulated setting the appropriate annual job loss indicator to zero, then they are simulated again setting

[47]Controls for multiple job loss were included in this model, as there were many parents suffering multiple job losses in the data.

the indicator to one. The difference between the two simulated probabilities, averaged over all youth who suffered from the particular shock, is the estimated treatment on the treated effect[48]. For further details of how the simulations were undertaken, see Appendix C.

Looking at the top panel of Table 10, parental job loss at age 16 leads to immediate increases in high school dropout behaviour. The probability of dropping out of high school at age 17 is 4.6 percentage points higher for youth who suffer from the shock. This is a large impact as it doubles the average dropout rate at this age in the sample. It is only statistically significant at the 17% level, however. The rate of attendance at other post-secondary education also increases markedly. This increase is primarily observed in Quebec with higher rates of attendance at *CEGEP*s. Turning now to the second panel, parental job loss at age 17 also increases school dropout behaviour by age 18, and the impact here is statistically significant.

In the bottom panel of Table 10, the impacts of job loss on the education attendance of youth by age 19 or 20 (the final age in this study) are presented. Parental job loss at age 16 and age 18 have significant and large negative impacts on university attendance. This decrease in university attendance is offset by increases in attendance at other post-secondary education, particularly for age 18 shocks. Age 18 shocks also significantly increase school dropout behaviour, with the probability of not graduating high school and not attending PSE twelve percentage points higher. This is again a large impact, doubling the school dropout rate. Age 16 shocks also increase school dropout rates at the end of the period. Youth who dropped out of school straight after the shock at age 16 did not return later to complete high school.

I re-estimated this grade transition model including annual changes in parental income in place of the job loss indicators. These measures had no significant impacts on any of the grade transitions. This is consistent with the multinomial-logit attendance model estimates of the

[48] The probability weights on individual youth were employed when forming these averages, as they were during model estimation.

previous section. Income changes may be dominated by transitory movements.

6.5 Test of Exogeneity of Job Loss Shocks

As discussed above, a primary concern when identifying the causal impact of parental income on education attendance is the presence of unobservable characteristics of parents which impact both parental income and child education outcomes. There may be similar concerns with parental job loss shocks. One test of whether these parental shock measures reflect unobserved parental characteristics is to determine whether the observed shocks influence youth education transitions prior to when the shocks actually occur. This test is related to one of the procedures employed by Mayer (1997). She included measures of income from after an education outcome as a control for these unobserved characteristics.

I constructed this exogeneity test as follows. Age 18 job loss indicators were entered into the first and second transition equations, and age 17 job loss indicators were entered into the first transition equations. An indicator of whether parents suffered a job loss at any age of the youth from 16 through 18 was also placed in the initial condition (grade in school at age 16) equation. Tests of the joint significance of these added job loss measures failed to reject the null hypothesis that these additional shock measures had no impact on any of these earlier education transitions[49]. The test statistic had a probability value of only 0.405. It was constructed as a likelihood ratio test of the joint statistical significance of the additional ten parameters in the model.

Including these job loss indicators in the model did not alter the impacts of the relevant

[49] This exogeneity test may fail for reasons other than unobserved heterogeneity. It may fail if there is state dependence in these parental shocks. Some significant shock may have occurred prior to age 16, and due to state dependence we observe job losses in subsequent years. A significant relationship between these subsequent shocks and the initial condition may be picking up the effect of these earlier shocks. This failure will not occur in any of the subsequent education transitions, however, as there are measures of job loss included in those transitions already.

shocks on education transitions to any significant extent. The treatment on the treated simulations for the model with the post-transition job loss indicators included are presented in Table 11. This finding maintains my confidence that I am identifying the causal impact of persistent parental income shocks on youth education outcomes.

7 Discussion and Conclusions

Persistent shocks to parental income have considerable negative impacts on the education attendance of youth. Youth of high school leaving age whose parents lose their jobs are more likely to drop out of high school early and are less likely to attend university. These impacts may have significant and long-lasting effects on the economic well-being of these youth. Given the potential severity of these impacts, there may be a role for government intervention. Such intervention can be supported on both equity and efficiency grounds. The impact of parental job loss on high school dropout behaviour suggests that intervention may be required prior to post-secondary education entry.

The large negative impact of parental income shocks provides evidence of the importance of parental income in education attainment. There has been considerable debate about whether the observed correlation between parental income and education attainment of youth is actually causal. The evidence I find supports the case of a large causal impact. A ten thousand dollar persistent drop in annual parental income lowers the probability of a youth attending university by a considerable 6.6 percentage points. A temporary drop of the same magnitude lowers this probability by only 1.1 percentage points.

Previous research attempting to uncover a causal impact of parental income on education attainment have generally found much smaller effects than I have. Research employing sibling fixed effects strategies to uncover causal impacts use variation in income across siblings within a family. If the income variation used is dominated by temporary changes, it is not surprising that small impacts were found. Shea (2000) found small and insignificant causal effects of long run average parental income levels on the completed years of schooling of young adults. He employed exogenous job loss, union status and industry status of fathers to instrument long run parental income levels. I find a much larger impact from using job loss to indicate negative permanent income shocks. The difference reflects my focus on the impact of job loss on changes in income rather than on long run levels. I also focus on shocks at high school leaving age, whereas Shea analyzed average parental income levels over childhood. Income changes should reflect unexpected financial constraints more readily than long run average income levels[50].

Student loans were available to needy youth during the period I examine. Despite this, large impacts of parental income shocks on university attendance were identified. The evidence points to considerable financial constraints of some form on education attendance, but suggests that borrowing constraints alone may not be the only form that these financial constraints may take[51]. Individual investments in higher education are risky, and individual preferences for assuming large debt loads at young ages may be quite heterogeneous across the population. A proportion of youth may be averse to borrowing to invest in their own human capital even if the average expected financial payoff appears large. There are several risks involved, including course completion risk and income return risk (will the youth find a job that utilizes his higher

[50]The difference may also reflect the time period between the shock and the measured education outcome. I observe the immediate education responses of youth to parental job loss, while Shea considered only final years of schooling by age 25. Even if education attendance is only delayed by parental shocks, the costs to youth may be considerable, as they complete education later and earn higher wages over a shorter working life.

[51]On the other hand, these results may in part reflect an inflexibility in the Canadian student loan program. Eligibility is based on parental income, with the amount of loans available to potential students reduced as parental income increases. Potential borrowers must provide evidence of their parent's income by submitting their parent's tax returns for the previous calendar year. Negative shocks to income which occur in one year are generally not observed in tax returns till the following year. Students can appeal their eligibility determination given evidence of a considerable change in circumstances, such as parents losing full-time jobs. This process may delay receipt of funds, however.

education). Transfers of some kind, via parents or directly from governments, may be required to overcome the financial constraints a significant proportion of youth may face.

A Final SLID Sample Construction and Panel Attrition

The first two panels of the SLID include 2,909 longitudinal respondents of the appropriate age for inclusion in this study. This included youth aged 15 or 16 at the start of each panel from Quebec and Ontario, and youth aged 14, 15 or 16 from the remaining provinces. Just over one half of this total number of potential observations were not able to be employed in the analysis for a variety of reasons. The following is a list of sequential removal of observations and the reasons why they were removed. In total, 1,574 observations could not be used, representing 54% of the potential sample.

1. Youth not observed at age 16[52] - 4%.
2. Youth not residing at parental home at age 16, so no parental information available - 3%.
3. The family household the youth belonged to fell out of the sample - 11%.
4. The youth left the family household after age 16 and could not be contacted by Statistics Canada staff - 6%.
5. Youth did not answer education attendance questions for each year required even when contacted - 8%.
6. At least one covariate was not defined for the youth, e.g. average parental income, number of siblings, parental education - 4%.
7. Annual information on the employment outcomes of the main income earner of the family were not available for each year required - 14%.
8. The annual education transitions reported by the youth suggested errors in reporting - 4%.

Attendance information was imputed for a small number of survey respondents where missing observations were encountered. This was undertaken to minimize sample attrition, and was only followed for youth at ages 16 and 17 where subsequent annual attendance reports justified imputation. Imputation involved attributing high school attendance to youth at age 16 or 17 who were subsequently enrolled at high school at the next annual survey.

Table 12 provides summary information on the sample employed and on the observations that could not be used, where possible. The parental income measure here is for the one year (rather than a three year average) when the youth was aged 16, or the nearest younger age if no details were available at age 16. The characteristics of youth not employed in the analysis is only different to the characteristics of those included in some dimensions. They are more likely to be from a lone parent family, to have less educated parents, and less likely to

[52] A small percentage of youth were not observed at age 16. This will occur if the household the youth belonged to fell out of the longitudinal survey prior to the youth turning 16.

be city residents. Their exclusion from the analysis should only result in biased estimates of the impact of tuition on inequality if there is some unmeasured characteristics of these youth related to their exclusion from the sample, their education attendance, and to their individual characteristics or background.

One check on the representativeness of the final sample employed in the analysis is to compare the education outcomes of these youth with the education outcomes of a separate sample of youth of the same age. The Canadian Census was employed for this purpose. Education attendance rates for the SLID sample employed here and equivalently aged youth from the 1996 Census Public Use file were similar. The SLID sample of youth generally were more likely to be students at other post-secondary education institutions, but university attendance rates were the same.

B Covariates and Data Sources

B.1 Covariates

Here is a description of the various covariates included in the analysis. Summary statistics are provided in Table 4. The French Mother Tongue variable indicates whether the youth's first language spoken is French. The aboriginal descent indicator is a self-report of belonging to one of the several indigenous populations in Canada. If either parent was not born in Canada, the parent immigrant indicator was set to one. Visible minority status is a self report. The lone parent indicator is set to one if the youth lived with only one parent at age 16. The children in family variable measures the number of children ever born or raised by the female parent. If the youth belonged to a single parent family headed by a male, then the number of children ever raised by this male parent was employed. The first parental education indicator denotes that neither parent (or the one parent if a single parent family) graduated from high school. The second denotes that at least one parent completed some kind of post-secondary degree, but neither completed a university bachelors degree or higher. The third indicator denotes that at least one parent completed a university bachelors degree or higher.

Parental income was calculated as the average annual real[53] parental income after tax over the three years when the youth was aged 16, 17 and 18. The parentage of youth was determined by the family structure of the household when the youth was aged 16, i.e. whether the youth lived with both parents or only one. Living costs vary considerably across Canada. For example, rent is much higher in the city of Vancouver than in rural Saskatchewan. Statistics Canada constructs annual measures of Low Income Cut-offs (LICOs). These measures vary by family size and size of the area of residence. Differences in these LICO measures between rural and urban areas reflect differences in costs of living. These measures were employed to adjust parental income for living cost differences prior to splitting youth into parental income quan-

[53] Nominal income measures were deflated by the Canada-wide CPI index.

tiles. Youth were divided into three equal groups (high, middle and low) by average real after tax parental income in excess of the appropriate LICO measure for the household. This procedure resulted in denoting youth with real (2001 dollar) unadjusted pre-tax parental income below approximately $40,000 as low income. High income youth are those with parental income above approximately $70,000. Indicators of these income quantiles and a spline in the adjusted parental income measure (adjusted income interacted with the quantile indicators) were included in the post-secondary education attendance model estimates of Section 5.

The city and rural area indicators refer to the size of the area of residence when the youth is 16. The remainder of youth reside in small urban areas, i.e. cities and towns with less than 100,000 residents. There are three indicators for whether the residence of the youth at age 16 was further than 40 and 80 kilometres (25 and 50 miles) from the nearest university or college (community college or *CEGEP*). Very few individuals live beyond 80 kilometres of a college in Canada.

The measures of real college and university tuition are averages across institutions within each province in the year that the youth would normally enter college or university respectively. The university provided financial aid variable captures the impact of scholarships and bursaries on the demand for university education in certain provinces. Separate measures of scholarship (merit-based) and bursary (need-based) funding were unavailable. This variable is calculated as the annual total amount of financial aid (in 2000/01 dollars) provided directly by universities in a province divided by the total number of full-time university students in that province and year. It thus measures the average expected amount of such financial aid for a youth attending university. The unemployment rate refers to the provincial rate in the year the youth would normally enter university or college.

B.2 Data Sources

The vast majority of variables employed in this analysis were constructed directly from the SLID internal use data sets made available via the Statistics Canada Research Data Centre at the University of British Columbia. The sources employed during construction of variables not taken from the SLID are listed below.

1. Parental income measures were adjusted using Low Income Cutoff (LICO) measures by size of area of residence and family size taken from the Statistics Canada publication authored by Paquet (2002).

2. Distances to closest PSE institutions (universities and colleges) were constructed using the latitude and longitude of the place of residence of each youth at age 16 taken from the SLID. The latitude and longitude of PSE institutions was constructed using a database of the postal code of each institution in Canada compiled by Marc Frenette of Statistics Canada (see Frenette (2003) for details). Postal codes were transformed into latitude

and longitude measures using the Postal Code Conversion File (PCCF) database from Statistics Canada. Straight line distances were constructed using the following formula:

$$Distance = 6,370.997 * \cos^{-1}[\sin(lat_y) * \sin(lat_i) + \cos(lat_y) * \cos(lat_i) * \cos(long_y - long_i)]$$

In this equation, the latitude (lat) and longitude ($long$) numbers were measured in radians by dividing the original latitude and longitude measures in degrees and decimals by 57.29577951. The subscripts y and i refer to the locations of youths and PSE institutions respectively.

3. Annual average college tuition by province were obtained from statistics reported by the Manitoba Council on Post-Secondary Education. These provincial averages were not weighted within each province, but tuition at publicly funded colleges varied little within provinces. See http://www.copse.mb.ca/en/documents/statistics/index.htm for the data.

4. Annual average university tuition by province were constructed from individual university tuition fees for undergraduate arts programs (within-province students) collected by Statistics Canada. Data from 1994/95 were provided directly by Statistics Canada's Centre for Education Statistics. Prior to 1994/95, fees were taken from data release entitled "Tuition and living accommodation costs for full-time students at Canadian degree granting institutions". Averages within each province were calculated using 1997/98 total full-time enrolment numbers as weights. University enrolment numbers were also sourced from Statistics Canada, using Cansim cross-tabulation 580701.

5. Annual Provincial unemployment rates were taken from Statistics Canada's Cansim II table 282-0002.

6. Annual aggregate university-provided financial aid by university was provided by Statistics Canada's Centre for Education Statistics. These numbers were aggregated within provinces then divided by aggregate full-time enrolment at universities within each province.

7. All variables that were constructed in real terms used the Canada-wide Consumer Price Index, sourced from Cansim II table 326-0001.

C Grade Transition Model Details

C.1 The Likelihood Function and Estimation

The likelihood function I estimate is described here. It is taken directly from Appendix B in Cameron and Heckman (2001). The notation set out in Section 6.2 is followed. Denote $d_{a,j_a,c}$

as the realized value of $D_{a,j_a,c}$. Abbreviate the initial condition to $d_{\underline{a},c}$. Note that the schooling status at age a (denoted j_a) is equal to the choice made at age $a-1$, which is denoted c_{a-1}. Define a history H of education outcomes for an individual:

$$H \;=\; (D_{\underline{a},c} = d_{\underline{a},c},\; D_{\underline{a}+1,c_{\underline{a}},c} = d_{\underline{a}+1,c_{\underline{a}},c},\; ...,\; D_{\overline{a},c_{\overline{a}-1},c} = d_{\overline{a},c_{\overline{a}-1},c})$$

Conditioning on the observables Z and a particular value for the unobservable η_i, the probability of observing the above history is:

$$\begin{aligned}\Pr(H|Z,\eta_i) \;=\; &\prod_{c\in C_{\underline{a}}}[\Pr(D_{\underline{a},c} = d_{\underline{a},c}|Z_{\underline{a}},\eta_i)]^{d_{\underline{a},c}} \cdot \prod_{c\in C_{\underline{a}+1,c_{\underline{a}}}}[\Pr(D_{\underline{a}+1,c_{\underline{a}},c} = d_{\underline{a}+1,c_{\underline{a}},c}|Z_{\underline{a}+1},\eta_i)]^{d_{\underline{a}+1,c_{\underline{a}},c}} \\ &\cdots \prod_{c\in C_{\overline{a},c_{\overline{a}-1}}}[\Pr(D_{\overline{a},c_{\overline{a}-1},c} = d_{\overline{a},c_{\overline{a}-1},c}|Z_{\overline{a}},\eta_i)]^{d_{\overline{a},c_{\overline{a}-1},c}} \qquad (14)\end{aligned}$$

At each age after the initial condition ($a \in \{\underline{a}+1,...,\overline{a}\}$) there is a separate probability product term for each schooling status c_{a-1}. The superscript variables ($d_{\underline{a},c}$, etcetera) are indicators which pick out the appropriate elements of the education history H for a particular observation. The probability of each education transition and the initial condition are modelled using the functional form in equation 10. The log-likelihood function L that is maximized during estimation is:

$$L \;=\; \ln\left[\sum_{i=1}^{I}\Pr(i)\cdot\Pr(H|Z,\eta_i)\right] \qquad (15)$$

Here the probability $\Pr(i) \geq 0$ is the one associated with the mass point η_i, and where $\sum_{i=1}^{I}\Pr(i) = 1$ is imposed. Estimation revealed that two mass points ($I = 2$) were sufficient to characterize the data. This finding is consistent with other studies employing this random effects estimation technique. Estimation involved setting $\eta_1 = 0$ and $\eta_2 = 1$. I estimated the probability $\Pr(1)$, setting $\Pr(2) = 1 - \Pr(1)$. The distribution of η was estimated recursively, identifying $\Pr(1)$ off estimation of the initial condition at age 16.

To identify the variable coefficients (the βs) and the factor loadings on the unobservable (the αs), one choice within each choice set must have its coefficient and factor loading values normalized in order to identify the remaining parameters. Denote the choice c_a^* as the normalization. The parameters β_{a,c_a-1,c^*} and factor loading α_{a,c_a-1,c^*} were then constrained to zero within each choice set. As a result of this normalization, the remaining estimated coefficients and factor loadings are defined relative to those for the normalization case. Estimation of the model parameters involved searching among a set of starting values for the probability and the factor loadings (the αs). This was necessary as the log likelihood function L is not guaranteed to be globally concave.

C.2 Forming the Transitions and Estimation Details

Here are some specific details about how the education transitions undertaken by youth were constructed, and more details on how transitions were modelled.

A number of youth in the sample reported completion of eight years or less of school by age 16. These youth were re-classified as completing nine years with little loss to the model's ability to capture attendance outcomes while considerably savings in model parsimony. A larger number of youth reported completion of eleven years of school by age 16. These reports were generally at odds with other information in the SLID provided by the parents on the grade the youth was attending at age 15. This information was not reported for all youth during all years of the SLID so could not be used in estimation. These reports were also at odds with the normal education path of Canadian youth, who generally begin the first grade of school at age 6. It suggests that some youth may have considered the kindergarten year as a year of elementary school, leading to an overestimation of the number of years of school completed at age 16 by one. These youth were re-classified as completing ten years of school. A very small number of youth reported completion of twelve or thirteen years of school, or reported attendance at college and university, at age 16. These youth were excluded from the analysis. A small number of youth also reported subsequent education transitions that did not accord with a normal education progression. For example, some youth reported completion of grade nine at age 16, and university attendance at age 17. Such unusual transitions were deemed reporting error, so those observations were also excluded from the analysis.

Reporting of high school graduation status in the SLID did not appear accurate. Graduation rates were much lower than in other Canadian surveys such as the Census. Not all youth are asked if they graduated high school each year in the SLID. They are only asked this question if they answered prior questions on high school attendance in a particular way. This may have resulted in this under-reporting of graduation status, particularly for youth who attend some type of post-secondary education directly after completing high school. High school graduation status was not used as a pre-requisite for university attendance during model estimation. High school graduation information was used in the model for youth who did not go on immediately to post-secondary education. For example, youth who reported attending grade twelve at age 18 but no receipt of a high school graduation certificate were modelled separately from those reporting such receipt. The third transitions of these two groups were quite different, with the latter much more likely to attend university for the first time at age 19.

Given the different schooling structure in Quebec, grade transitions were modelled separately for youth from that province. The majority of youth in Quebec often choose to enter a *CEGEP* after completion of the 11th grade of school. They can then complete two years of *CEGEP* to gain the prerequisites for university entrance. Studies at a *CEGEP* are generally broken into two streams: the academic stream and the vocational stream. Those youth undertaking the former can gain the prerequisites for university entry. Those undertaking the latter gain vocational (for example a trade) skills but do not gain the university entrance requirements. The choice of stream is not reported in the SLID micro data.

Youth in grade 11 in Ontario at age 17 are much less likely to go to university after only 12 years of school. The majority of universities in that province required a thirteenth year of study at school for gaining university entrance pre-requisites. To allow for this, this transition was modelled separately for Ontarian youth at this age and grade.

C.3 Simulation Details

The grade transition model parameter estimates were employed to construct treatment on the treated effects in response to parental income shocks. Construction of these effects involved simulating the impact of the parental shock on the predicted probability of each annual education outcome for each youth in the sub-sample of those who suffered from the parental income shock.

I simulate the model in a sequential set of steps. First, I calculate a fitted probability of being in grade nine or grade ten at age 16 for each youth in the sub-sample, given their characteristics and the estimates from the initial condition equation. This calculated probability is compared with a random draw from a uniform distribution on [0, 1] to assign an appropriate initial grade status to each sub-sample member. Those youth assigned to grade ten status are then used to calculate a fitted probability of making each possible education transition (to dropout, grade 11 or to other PSE) again employing their individual characteristics and using the parameter estimates from the appropriate MNL equation for grade ten youth at age 16. Those fitted probabilities are compared to another random draw from U[0, 1] in order to assign an appropriate age 17 status for those individuals. The same procedure is used to simulate education transitions for youth assigned to grade nine status at age 16.

The process continues for each education transition in a similar manner, where assigned education status at one age determines which transition probabilities are simulated at the next age for that individual. These simulations are conducted 200 times for each individual in the sub-sample. The average of the simulated probabilities across all individuals and across these 200 repetitions are then calculated, for each possible education status at each age.

The simulations were all constructed twice. First, the simulations were undertaken setting the parental shock indicator to zero for all youth in the sub-sample. The simulations were then undertaken again setting the parental shock indicator back to one. The difference in the simulated probabilities of each annual education outcome is the measure of the treatment on the treated effects.

To construct standard errors on these simulated treatment on the treated effects, the same simulation exercise was followed for five hundred random draws from the estimated distribution of the parameters. The inverse hessian was employed as the appropriate variance-covariance matrix of the estimated grade transition model parameters following Cameron and Heckman (2001). The parameter estimates were assumed to be normally distributed when taking these random draws. In particular, a Choleski decomposition was taken of the estimated variance-covariance matrix. This decomposition matrix was multiplied by a vector of independent draws from a standard normal distribution, then added to the vector of parameter estimates to form one random draw from the estimated distribution of parameters.

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Table 1: **Post-Secondary Education Attendance Rates**

	All Youth	Parental Income Low	Medium	High
University	0.30	0.20	0.28	0.41
Other PSE	0.35	0.32	0.39	0.33
Neither	0.35	0.48	0.33	0.26
Observations	1,335			

Source: Survey of Labour and Income Dynamics.

Table 2: **Parental Job Loss - Prevalence**

	Age 16	Age 17	Age 18	Any age from 16 to 18
Main Income Earner	0.091	0.082	0.058	0.110
Spouse of MIE	0.099	0.088	0.070	0.127
Observations	1,335			

Source: Survey of Labour and Income Dynamics.

Table 3: **Parental Income Changes - Percentiles of Distribution**

	16 to 17 change	17 to 18 change	18 to 19 change	Change from age 16 to 19
Dollar changes ($000s)				
5%	-15.7	-17.3	-18.7	-24.1
10%	-9.5	-9.6	-10.4	-14.4
25%	-2.9	-3.5	-3.5	-4.6
50%	0.2	0.3	0.0	0.8
75%	4.5	4.8	4.4	8.5
90%	11.2	11.8	10.8	19.1
95%	20.5	19.0	18.6	29.9
Percentage changes				
5%	-40.1	-41.3	-43.5	-55.7
10%	-22.4	-22.0	-26.9	-35.6
25%	-6.9	-7.5	-8.8	-11.6
50%	0.5	0.7	-0.1	1.9
75%	10.6	10.6	8.6	17.0
90%	25.3	32.1	25.5	46.5
95%	45.9	61.1	52.0	84.9
Observations	1,335			

Source: Survey of Labour and Income Dynamics.

Table 4: **Regressors in Model - Summary Statistics**

Variable	Mean	Standard Deviation
Female	0.488	
French mother tongue	0.203	
Aboriginal descent	0.028	
Visible minority	0.087	
Parent immigrant	0.236	
Lone parent	0.151	
Parents not graduate HS	0.119	
Parents other PSE only	0.448	
Parent completed university	0.190	
Real average parental income ($000s)	65.93	43.96
Children in family	2.79	1.56
City resident ($\geq$ 100,000)	0.533	
Rural resident	0.169	
University more than 80 km away	0.190	
College more than 40 km away	0.137	
Real college tuition ($100)	12.49	6.79
Real university tuition ($100)	29.44	7.70
Unemployment rate	7.87	2.90
University financial aid ($100 per stud.)	6.55	2.72
Observations	1,335	

Sources: Survey of Labour and Income Dynamics and Statistics Canada (see Appendix B for details).

Table 5: **University Attendance - MNL Marginal Effects**

Shock Included Variable	Income change age 18 to 19	Income change age 16 to 19	MIE Job Loss Any age 16 to 18
Female	21.5*** (3.3)	22.1*** (3.5)	22.5*** (3.5)
French-speaking	-9.2** (4.5)	-9.4** (4.4)	-9.2** (4.4)
Aboriginal descent	-17.1*** (6.0)	-16.9*** (5.9)	-18.1*** (6.2)
Visible minority	15.6 (11.4)	15.6 (11.3)	20.6* (12.4)
Immigrant parent	12.1* (6.9)	11.8* (6.7)	10.6 (6.8)
Dependent children	-0.8 (1.7)	-0.8 (1.6)	-1.1 (1.8)
Lone parent	-11** (4.9)	-10.9** (4.8)	-11.8** (5.0)
Parents no HS	-8.3 (6.9)	-8.2 (6.8)	-9.5 (7.2)
Parents other PSE	3.5 (3.0)	3.2 (3.1)	3.6 (3.1)
Parent University	35.3*** (6.1)	34.1*** (6.1)	34.1*** (6.2)
Low parent inc.	-6.9* (4.0)	-6.8* (4.0)	-6.2 (4.3)
High parent inc.	3.1 (3.8)	3.1 (3.5)	3.5 (3.9)
Univ. over 80km	-5 (5.7)	-5.1 (5.6)	-5.3 (5.7)
College over 40km	3.5 (5.9)	4.1 (6.2)	3.9 (5.9)
College tuition	-4.8** (2.3)	-4.9** (2.3)	-5** (2.4)
University tuition	-3.8 (2.3)	-3.6 (2.3)	-3.5 (2.5)
Unemployment rate	-0.9 (2.2)	-0.5 (2.2)	-0.5 (2.4)
University financial aid	-0.2 (2.1)	-0.6 (2.1)	-0.9 (2.2)
Shock measure	-1 (0.7)	-1.4* (0.8)	-10** (4.7)

Note: One, two and three asterisks (*) denote significance at 10%, 5% and 1% levels resp. Gender specific time trends, regional indicators, and city and rural indicators also included.

Table 6: **Other PSE Attendance - MNL Marginal Effects**

Shock Included Variable	Income change age 18 to 19	Income change age 16 to 19	MIE Job Loss Any age 16 to 18
Female	3.7 (3.5)	3.5 (3.5)	3.1 (3.6)
French-speaking	9.3 (7.6)	9 (7.6)	6.3 (7.3)
Aboriginal descent	-9.8 (6.1)	-9.6 (6.3)	-9.6 (6.4)
Visible minority	8.9 (9.8)	9.2 (9.9)	6.3 (9.2)
Immigrant parent	1.6 (5.6)	1.7 (5.7)	2.3 (6.0)
Dependent children	0.4 (0.8)	0.4 (0.8)	0.4 (0.7)
Lone parent	-4.6 (4.0)	-4.3 (4.0)	-3.9 (4.1)
Parents no HS	-5.4 (5.0)	-5.4 (4.9)	-5.9 (5.1)
Parents other PSE	6.1 (4.5)	6.1 (4.6)	5.9 (4.7)
Parent University	-1 (4.8)	-0.9 (4.9)	-1.5 (5.0)
Low parent inc.	-2.9 (4.2)	-2.9 (4.1)	-2.9 (4.2)
High parent inc.	-0.8 (3.8)	-0.3 (3.8)	-1 (3.8)
Univ. over 80km	-4.2 (4.2)	-4.3 (4.2)	-4.3 (4.3)
College over 40km	1.5 (3.4)	1.5 (3.3)	1.3 (3.4)
College tuition	-2.1 (2.4)	-2.1 (2.5)	-1.6 (2.5)
University tuition	1.1 (3.1)	1 (3.1)	0.5 (3.0)
Unemployment rate	-2.3 (2.2)	-2.1 (2.3)	-2.8 (2.3)
University financial aid	6.2*** (2.2)	6.1*** (2.2)	6.7*** (2.3)
Shock measure	0.6 (0.7)	-0.4 (0.8)	-4.1 (6.2)

Note: One, two and three asterisks (*) denote significance at 10%, 5% and 1% levels resp. Gender specific time trends, regional indicators, and city and rural indicators also included.

Table 7: **Parental Shocks and PSE Attendance - MNL Marginal Effects**

	University	Other PSE	No PSE
Income changes (-$10,000)			
age 18 to 19	-1 (0.7)	0.6 (0.7)	0.4 (1.0)
age 17 to 18	-0.9 (1.4)	-0.2 (0.8)	1.1 (1.5)
age 16 to 17	0.5 (0.7)	-1.1 (1.3)	0.5 (1.4)
age 16 to 19	-1.4* (0.8)	-0.4 (0.8)	1.8 (1.1)
Job loss - any age 16 to 18			
Main income earner	-10** (4.7)	-4.1 (6.2)	14.1** (6.2)
Spouse of MIE	1.1 (6.4)	2.9 (4.8)	-4 (7.2)
Observations	1,335		

Note: One, two and three asterisks (*) denote statistical significance of these differences at the 10%, 5% and 1% levels respectively.

Table 8: **Permanent and Temporary Parental Income Shocks - MNL Marginal Effects**

	University	Other PSE	No PSE
Permanent (-$10,000)	-6.6** (3.2)	-2.4 (3.4)	8.9** (4.2)
Temporary (-$10,000)	-1.1 (0.7)	-0.3 (0.8)	1.3 (1.1)
Observations	1,335		

Note: One, two and three asterisks (*) denote statistical significance of these differences at the 10%, 5% and 1% levels respectively.

Table 9: **Breakdown of Parental Job Loss Impacts - MNL Marginal Effects**

	University	Other PSE	No PSE
Parent HS or less * job loss	-17.3**	-15.8***	33.2***
	(7.9)	(5.4)	(9.0)
Parent PSE * job loss	-2.2	11.4	-9.2
	(5.6)	(11.2)	(10.0)
Parental age (5 yr inc.)	0.6**	0	-0.6
	(0.3)	(0.3)	(0.4)
Job loss	-10.1**	-3.8	13.9**
	(4.6)	(6.0)	(6.3)
Age (5 yr inc.) * job loss	0.6	0.1	-0.7
	(1.0)	(1.1)	(1.3)
Observations	1,335		

Note: One, two and three asterisks (*) denote statistical significance of these differences at the 10%, 5% and 1% levels respectively.

Table 10: **Job Loss Shocks - Treatment on the Treated Effects**

	Age 16 shock	Age 17 shock	Age 18 shock
Age 17 Outcome			
Dropout	4.6 (3.1)		
Still in H.S.	-9*** (3.4)		
Other PSE	4.5*** (1.4)		
Age 18 Outcome			
Dropout	4.2 (2.6)	4.9** (2.2)	
Still in H.S.	-12.5** (5.3)	-11.2 (7.5)	
Other PSE	5.5 (4.5)	6.5 (4.2)	
University	2.8 (2.8)	-0.3 (6.4)	
Final Outcome			
Dropout	5.7** (2.6)	0 (6.8)	12.3*** (3.7)
Still in H.S.	-1.8 (1.2)	-4.2 (4.5)	1.9 (1.7)
H.S. graduate	3.2 (3.8)	-0.1 (8.7)	-13* (7.5)
Other PSE	4.9 (3.9)	5.3 (6.5)	14.3*** (4.4)
University	-12.1** (5.0)	-1 (18.4)	-15.5** (6.8)
Any PSE	-7.2 (4.8)	4.2 (14.6)	-1.1 (6.3)

Note: One, two and three asterisks (*) denote statistical significance of these treatment effects at the 10%, 5% and 1% respectively. Standard errors constructed taking 500 random draws from estimated distribution of model parameters (inverse hessian) and simulating treatment effect using each random draw. Parameters assumed normally distributed when taking random draws.

Table 11: **Test of Exogeneity of Job Loss Shocks**

	Age 16 shock	Age 17 shock	Age 18 shock
Age 17 Outcome			
Dropout	4.9 (3.1)		
Still in H.S.	-9.5*** (3.3)		
Other PSE	4.6*** (1.7)		
Age 18 Outcome			
Dropout	4.2* (2.4)	4.3** (1.7)	
Still in H.S.	-11.1** (5.3)	-7.1 (7.5)	
Other PSE	5.2 (4.9)	6 (4.2)	
University	1.7 (2.9)	-3.2 (7.0)	
Final Outcome			
Dropout	6.4** (2.7)	0.6 (6.4)	12.4*** (3.3)
Still in H.S.	-0.6 (1.3)	-3.7 (4.5)	3.6* (2.0)
H.S. graduate	2.4 (3.9)	0 (8.9)	-15* (7.9)
Other PSE	3.5 (4.2)	7 (6.1)	15.7*** (5.0)
University	-11.6** (4.9)	-3.9 (16.7)	-16.6** (7.3)
Any PSE	-8.2* (4.9)	3.1 (13.7)	-0.9 (6.3)
Exogeneity Test	stat.=8.36	dist. χ^2_{10}	p-val=0.405

Note: One, two and three asterisks (*) denote statistical significance of these treatment effects at the 10%, 5% and 1% respectively.

Table 12: **Summary Statistics for Final Sample Analyzed and Dropped Observations**

Variable	Sample Used Mean	Sample Used Stand. Dev.	Dropped Observations Mean	Dropped Observations Stand. Dev.	Obs.
Female	0.488		0.485		1,574
French mother tongue	0.203		0.205		1,574
Aboriginal descent	0.028		0.030		1,574
Visible minority	0.087		0.109		1,574
Parent immigrant	0.236		0.246		1,574
Lone parent	0.151		0.224		1,498
Parents not graduate HS	0.119		0.169		1,500
Parents other PS only	0.448		0.409		1,500
Parent completed university	0.190		0.167		1,500
Real parental income ($000s)	64.70	42.76	62.77	45.71	1,498
Number of children in family	2.79	1.56	2.80	1.41	1,435
City resident ($\geq$ 100,000)	0.533		0.628		1,574
Rural resident	0.169		0.121		1,574
University more than 80km away	0.190		0.158		1,574
College more than 40km away	0.137		0.112		1,574
Atlantic	0.132		0.093		1,574
Quebec	0.194		0.244		1,574
Ontario	0.282		0.319		1,574
Prairies	0.224		0.209		1,574
BC	0.168		0.134		1,574
Observations	1,335				

Source: Survey of Labour and Income Dynamics.

Figure One

Real Tuition

2000/01 dollars

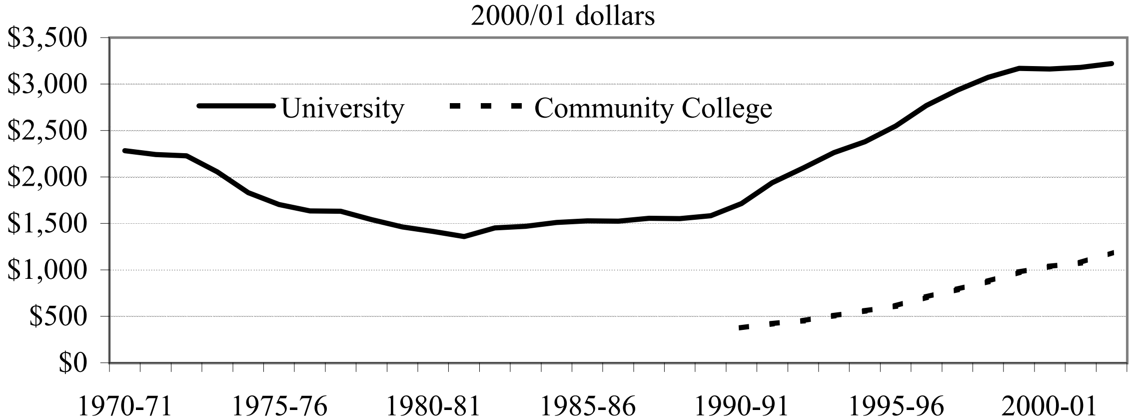

Figure Two (a)

Full-time University Enrolment

% of population aged 18-24

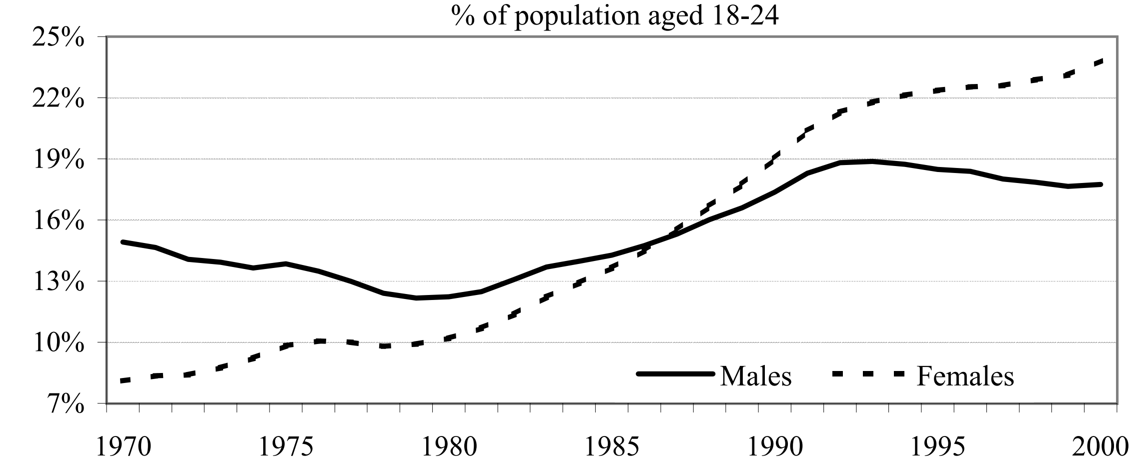

Figure Two (b)

Full-time Community College Enrolment

% of population aged 18-24

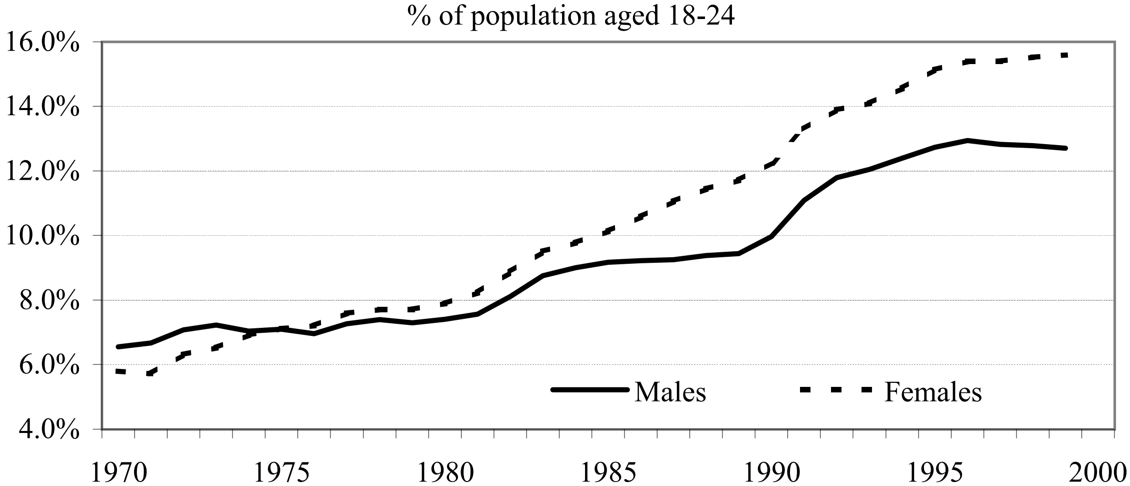

Figure Three: Grade Transition Model - Subset of Transitions