Discontinuities in post-secondary schooling and wage gap

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Abstract

The paper studies the impact of both permanent and temporary school post-secondary interruptions on wages. While most studies focus on the impact of permanent interruptions, little attention has been accorded so far to the impact of temporary school interruptions. There is however substantial empirical evidence that educational trajectories are discontinuous with episodes of temporary interruptions and re-enrollments. Using longitudinal data from two distinct cohorts of the Youth in Transition Survey in Canada, we provide empirical evidence on the impact of both permanent and temporary school interruptions. Our results are robust across these cohorts and show that there is a very slight wage penalty -less than 5%- associated to both permanent and temporary post-secondary interruption. Our study, however, shows that the wage of temporary interrupters evolves very rapidly compared to leavers and continuers. Indeed, temporary interrupters may benefit from better prospects on the labor market to tailor conveniently their skills. These results are relevant for educational policies.

1 Introduction

Educational attainment is an important component that affects several economic and labor market outcomes such as wages, occupation and unemployment. The human capital theory and the signal theory both offer interesting frameworks to analyze the impact of the level of education on labor market outcomes particularly wages. The impact of educational attainment on wages is well investigated in regard to the estimation of the return of schooling in many studies (Card, 2001; Heckman et al., 2008; Carneiro et al., 2011).

The standard human capital theory (Becker, 1964; Mincer, 1974) predicts that dropping out from school leads to a wage penalty. The level of education in such analysis is implicitly considered linear and continuous regardless of probable discontinuous trajectories (temporary interruptions). School interruptions in this analysis are generally regarded as permanent with no consideration of re-enrollment later. Hence most studies focus on the impact of permanent interruptions on wages and little attention has been so far given to the impact of temporary school interruptions on wages (Fortin and Ragued, 2017).

Education attainment, however, is not always linear and continuous, it can be characterized with discontinuities (presence of temporary interruptions and re-enrollment). Indeed, some students decide to temporarily interrupt studies for various reasons (work, travel, illness, financial problems, change of program or establishment, etc.). Several studies report substantial numbers of dropouts who re-enroll and pursue their education later (Lambert et al., 2004; Stratton et al., 2008; Raymond, 2008; Fortin et al., 2019). For instance, Lambert et al. (2004) found that almost 40% of canadian youths who left post-secondary education at the age of 18 to 20 had returned two years later. At the post-secondary level, about 40% of canadian university dropouts and 54% of college dropouts are temporary (Fortin et al., 2019).

These discontinuities can't be ignored as they affect education and labor market outcomes. As remarked by Fortin and Ragued (2017), students with discontinuous schooling can indeed face less interesting career prospects because of a more limited or obsolete human capital (deterioration over time in value) and a negative signal effect to potential employers as they may convey a signal of lack of commitment, perseverance and motivation. On the other hand, a student who takes a break from formal education to travel around the world and gain a broader horizon on life may reveal character traits that are appreciated by employers.

Despite evidence of high numbers of temporary school interruptions and its theoretical ambiguous effect on wages, empirical evidence on the subject is quite scant. One of the reasons behind this is the lack of suitable data to carry on such analysis. Indeed, we need a longitudinal/retrospective data where students are followed up in their educational trajectories and in the labor market. Light (1995b) uses data from the National Longitudinal Survey of Youth and finds that young men who interrupt their schooling receive wage boosts that are smaller than those received by their continuously enrolled counterparts. Other studies such as Griliches (1980); Marcus (1984) found no significant effects of discontinuous schooling on labor-market outcomes. Other studies again highlight positive returns of discontinuous schooling (Leigh and Gill, 1997; Ferrer and Menendez, 2014).

Fortin and Ragued (2017) showed that different reasons for interruption seem to balance one another in terms of impact on wages. Indeed, using the Canadian 2007 National Graduate Survey, they found a positive effect on wages of temporary schooling interruption for men who had held a full-time job during their out-of-school spell(s). Both men and women witness a wage decrease if their interruption is associated with health issues. Women also bear a wage penalty if their interruption is due to a part-time job, to lack of money, or is caused by reasons other than health, work, and money. Their analysis is, however, conducted on a cross-section data and

don't allow to conduct wage growth analysis. A longitudinal data, however, allows to analyze wage growths. Moreover, it enables us to account conveniently for individual time-invariant characteristics. In Canada, such data can be extracted from the Youth in Transition Survey (YITS). This study uses the YITS to examine the impact of permanent and temporary post-secondary interruptions on wages. We look into post-secondary wage disparities due to post-secondary interruption status. Compared to other studies on the matter, our study has the interesting feature to analyze in the same framework the impact of both permanent and temporary school interruptions on wages.

The panel structure of our data also allows us to observe dynamics in schooling status and wages enabling us to characterize wage growths. We pose as Light (1995b) that school interruption and/or re-enrollment are correlated with time-invariant personal characteristics, and not with transitory wage shocks. By exploiting the panel structure of the data, we resort to panel econometric strategies to analyze the impact of both permanent and temporary school interruptions on wages. We use two distinct cohorts of YITS : Cohort A and Cohort B. Cohort A was made up of high school students aged 15 as of December 1999, who completed biographical questionnaires during six successive biennial cycles. Aged between 18 and 20 as of January 1, 2000, Cohort B respondents were not necessarily enrolled in an academic program when the survey began. Indeed, Cohort B was selected from the Labor Force Survey (LFS). They were followed during five successive biennial cycles. Thus, the two cohorts varied not only in age, but also in their situations with regard to both the education system and the labor market at the start of the observation period.

Our results are robust across these cohorts and show that there is a very slight wage penalty less than 5% associated to both permanent and temporary post-secondary interruption. These results are in line with Griliches (1980) and Marcus (1984). They contrast those of Griliches and Mason (1972); Featherman and Carter (1976) and Light (1995b) who rather found a significant wage penalty. We also show that the wage trajectory of temporary interrupters evolves faster than that of non-interrupters. This result is consistent with that of Light (1995b) concerning the wage growth of temporary interrupters. Indeed, Light (1995b) finds that individuals who have just completed their re-enrollment earn significantly less than continuously schooled men. However, their wages grow quite rapidly during the post re-enrollment period and so the gap between temporary interrupters and non-interrupters closes over time. The contribution of this study is twofold. Firstly, we analyze the impact of both temporary and permanent interruption in the same framework. Secondly, we characterize wage growths according to post-secondary interruption status.

The next sections of the article proceed with a literature review. We present the data and descriptive analysis. Estimation of the wage gap between interrupters and non-interrupters follows. We finally provide concluding remarks and suggestions for further research.

2 Literature review

Our study relates to several branches of the human capital literature. We present a literature review on the empirical evidence of school interruption and re-enrollment, the determinants of school interruption and re-enrollment and empirical studies investigating wage gaps between interrupters and non-interrupters.

2.1 Empirical evidence on school interruption and re-enrollment

In the classic research on college degree attainment, three categories of college students are distinguished (Tinto, 1988) : Persisters (Continuers), Stopouts (Temporary Interrupters), and Dropouts (Leavers or Stayouts). Persisters are defined as students who continued toward their degree goals; Stopouts are those who withdrew from studies and subsequently returned; and Dropouts are those who withdrew from studies and never returned.

Most of the attrition literature on schooling decisions, however, assumes that education attainment is linear. Once students stop enrolling, they never return - the decision to withdraw from school is considered a permanent one. Some of the recent work in economics has focused on decisions to drop out of high school (see for instance Parent, 2006; Rumberger and Lamb, 2003; Eckstein and Wolpin, 1999). Others analyzed the decision to invest in higher education (see Belley et al., 2014; Drolet, 2005; Eckstein and Wolpin, 1999; Rivard et al., 2004; Christofides et al., 2001).

Inversely, much less attention has been paid to the temporary interruption behaviors due mainly to available data limitations. Indeed, many of the dataset used to analyze attrition in schooling report generally enrollment at only two points in time and thus are not able to identify those students who return to studies following an interruption. Others have samples with too few observations across individuals and/or time to permit analysis of such behavior (Montmarquette et al., 2001). Yet temporary interruption behaviors are not unusual. The emergence of rich panel new data sets - National Longitudinal Survey of Youth (NLSY) in the USA and the Youth in Transition Survey (YITS) in Canada - has enabled researchers to document substantial temporary interruption behaviors.

Spletzer (1990) used the National Longitudinal Survey of the High School Class of 1972 and found that nearly 30 percent of the respondents who graduated from college within seven years of completing high school interrupted their schooling along the way. O'toole et al. (2003) reports that about 30 percent of all students actively pursuing an academic degree interrupts their education for at least one term during the five years following initial enrollment. Horn (1998) also documents that almost 30% of students enrolled (but not necessarily seeking a degree) in either four-year colleges or two-year public schools interrupt during their first year, but that almost half of these interruptions are relatively short-lived (less than five years). This suggests that half of all first-year attrition is short-term in nature. She presents evidence that students who leave college before their second year and do not return for five years are older, are more likely to have children, and are more likely to work full time as compared to students who do return. Marcus (1986) reports that 28 percent of the respondents in the National Longitudinal Survey of Young Men who leave school by 1966 re-enroll by 1973. Using the same survey, Light (1995b) reports that 35 percent of white men in the NLSY who left school between 1979 and 1988 return back by 1989. In another study (Light, 1995a), she assumes that all interruptions are temporary and that, at some point, everyone will re-enroll. Exploiting the Youth in Transition Survey (YITS) in Canada, Lambert et al. (2004) find that almost 40% of young people who had abandoned their post-secondary studies as of December 1999 had already resumed two years later. Using the same database, Finnie and Qiu (2008) report about 40% of university dropouts and 54% of college dropouts are temporary. Raymond (2008) shows that approximately 35% of women who dropped out of high school went back to school, compared to 26% of men. Evidence that many young people undergo multiple transitions between school and work is also presented in Griliches (1980); Coleman (1984); Marcus (1984, 1986); Meyer and Wise (1984); Light (1995b,a) and Fortin et al. (2019).

2.2 Determinants of school interruption and re-enrollment

The substantial evidence of school interruption and re-enrollment has motivated several studies to investigate the determinants at play to explain dynamics in schooling decisions.

Regarding school interruption, numerous studies have stressed out the importance of parental background and family environment as one of the determinants of the probability of transiting from one grade level to the next. Empirical studies have found strong positive effects of family background variables on educational attainment. Family socioeconomic status, reflected in educational levels or occupation of parents, family income, or some combinations of these is found to increase (decrease) the likelihood of college enrollment and college graduation (college dropout) (Manski and Wise, 2013; Manski, 1989; Kane, 1994). Cameron and Heckman (1998) find that characteristics linked to the family environment such as income for example, are important determinants of school choices at all stages from the decision to complete elementary school and up to entry into post-secondary education. These findings demonstrate the significant influence of family background in determining youths educational attainment.

Another major determinant is unobserved individual heterogeneity, which represents factors such as individual specific schooling, academic ability, motivation, differences in discount rates or any other unobservable trait which is time-invariant (Belzil and Hansen, 2003). Controlling for these unobserved heterogeneity is important in models of educational attainment to mitigate potential selection bias (Willis and Rosen, 1979; Cameron and Heckman, 1998). The work of Cameron and Heckman (1998, 2001) shows how disregarding unobserved variables that are persistent over grade transitions generates serious biases in the estimated effects of family income on schooling. In their study, they recognize that education at any age is a result of previous school choice.

Hansen and Liu (2013a) developed and estimated a dynamic structural model of school decisions using YITS data. They studied the role of family environment variables, cognitive skills and future wages in shaping academic achievement in Canada. Their results show that financial resources play an important role in post-secondary education enrollment. Their model also showed how future wages affect current schooling decisions. They showed that a 25% increase in future wages for post-secondary graduates will increase post-secondary education by 2.2 percentage points for males and by 3.1 percentage points for females.

Regarding school re-enrollment, previous studies have established that the decision to go back to school is closely associated with labor supply decisions as well as earnings opportunities. Weiss (1971) argues that individuals who plan to switch jobs in response to changes in relative wages, may return to school in order to acquire new skills required by their new occupations. Corman (1983); Marcus (1986); Spletzer (1990) estimate discrete models of the rate of return to school for dropouts. Corman's model includes family income and local unemployment rates as explanatory variables. Marcus includes cumulative work experience and the differences between real and expected wages, while Spletzer introduces a variable indicating whether the individual is employed or not.

Light (1995b) documents that local unemployment rates and wage rates are important determinants of returning to school. She shows that return to school occurs when study costs are relatively low or that the returns to education are relatively high. Her results suggest that the age, number of brothers and sisters, the average level of tuition fees in the respondent's state of residence, wages and weekly hours worked are associated to lower probabilities of returning to school. Inversely aptitude test such scores such as the Armed Forces Qualification Test (AFQT), family income and unemployment rates have positive effects on the probability to

return to school.

Raymond (2008) estimates a linear probability model to analyze re-enrollment in high school. She finds that women drop out less than men. She also reports that women (35%) are more likely than men (26%) to return to school. The decision of women to re-enroll in school is influenced by the same reasons behind their school interruption, their motivation for a post-secondary diploma and time elapsed since their school interruption. For men, Raymond (2008) identified predictors such as labor market experience, previous education and post-secondary education aspiration. Laplante et al. (1983) confirmed the results of Raymond (2008) regarding the length of interruption and previous education as determinants of school re-enrollment. They also stress out a significant link between the socio-demographic characteristics of the individual, his living conditions and the decision to return to school. The authors, however, pointed out that their study was limited to describe the portrait of returning students. They didn't, however, address the motivations of adults who return to school after a period of interruption.

Finally, according to Light (1995b) , there is also a significant likelihood that time-invariant personal characteristics similar to those invoked in the mover-stayer model of job mobility elaborated by Blumen et al. (1955) might cause some individuals to transit into and out of school for reasons independent of their labor market opportunities. Though the question on the determinants of school interruption and re-enrollment is central and relevant for education policies, it is beyond the scope of this study. Our objective is to document the impact of both permanent and temporary interruptions on wages using recent canadian data.

2.3 Estimation of wage gaps

There is a mixed evidence regarding the impact of school interruptions and re-enrollment on wages. Some studies found a wage penalty or no effect due to school interruptions (Marcus, 1984; Monks, 1997; Light, 1995b; Griliches, 1980; Holmlund et al., 2008). Others rather found positive returns (Leigh and Gill, 1997; Ferrer and Menendez, 2014; Fortin and Ragued, 2017). Fortin and Ragued (2017) found similar results when the interruption is due to a full-time job. On the contrary, they show that there is a wage penalty if the interruption is due to reasons other than work. Fortin and Ragued (2017) argued that different reasons for interruption seem to balance one another in terms of impact on wages.

Precursors studies on the impact of school interruption on wages are Griliches and Mason (1972); Griliches (1980); Marcus (1984). Griliches and Mason (1972) conducted their analysis on a sample of post World War II veterans drawn from the 1964 Current Population Survey whose schooling interruptions were caused by military enlistment. The study of Griliches (1980) used data from the National Longitudinal Survey for years 1966-1970. The data contains reported information on completed schooling interruptions. Marcus (1984) used the same data as Griliches (1980) but extended to 1973.

Using the NLSY data relative to the year 1993 (when respondents were between 28 and 35, years of age), Leigh and Gill (1997) reported estimates of the incremental effect of community college education for returning adults in comparison to returns obtained by continuing high school graduates. They show that for Associate Degree community college, the returns of education are essentially of the same size for temporary interrupters and continuing high school graduate. Similarly among females, the estimated returns of non-degree community college programs are the same for both temporary interrupters and non-interrupters. However, among males in non-degree programs, temporary interrupters enjoy an incremental earnings effect of 8 to 10 percent above that

received by non-interrupters.

Light (1995b) employed a random effect approach to estimate a wage model that accounts for school and work discontinuities. She shows individuals who re-enroll in school earn less than their continuously schooled counterparts immediately upon returning to the workforce. This wage gap increases in function of the "waiting time" to the re-enrollment. Temporary interrupters, however, experience a rapid wage growth in their post-return period - closing the gap between their continuously schooled counterpart. For illustration, she shows that a college graduate whose schooling level advances from 12 years to 16 years but who delayed his enrollment by four years suffers a wage penalty of 17 percent compared to a non-interrupter who has 16 years and four years of work experience. Two years later, the gap shrinks to 13 percent and after another two years, it has virtually disappeared. Moreover, she shows that the more pre-return work experience temporary interrupters have, the faster this gap closes over time. Her analysis is, however, limited to white men.

Ferrer and Menendez (2014) used the 1995 Canadian National Survey of Graduates (NSG) to compare the returns on education of postsecondary graduates who delayed their tertiary education for some time and those who proceeded with no delays. They show that graduates who delayed their education enjoy a premium relative to graduates who completed their education with no interruptions even after considering other factors such as experience or labor market connections. They quantify that the returns to schooling interruptions between high school and college are 10 percent for bachelors degree holders and 14 percent for two-year degree holders.

Fortin and Ragued (2017) used data from the 2007 National Graduate Survey to investigate the impact of schooling discontinuities on post-graduation starting real wages. They report that temporary schooling interruption leads to an increase in starting wages for men who had worked full-time during their out-of-school spell. However if the interruption is due to health issues then both men and women experience rather a wage decrease. The study of Fortin and Ragued (2017) underscored that the impact of temporary school interruption on wages varies in function of the reasons behind the interruption (lack of money, health issues, full-time job, etc). And the effect of these different reasons balance one and another.

Overall, there is no consensus in literature on the impact of school interruptions on wages. Part of these contradictory results may be related to different survey designs and data characteristics but importantly to different definitions given to school interruption. While some consider delays between two diplomas (high school and college) as a school interruption (Ferrer and Menendez, 2014; Holmlund et al., 2008), others rather consider a school interruption as any discontinuity in schooling apart from normal break of summer and holidays observed before graduation. We retain this latter definition and compared to previous studies, we analyze the impact of both temporary and permanent interruption in the same framework. Doing so allows for richer analysis.

3 The YITS Data

This study uses data from the Youth in Transition Survey (YITS) to analyze the impact of both permanent and temporary school interruptions on wages. The Youth in Transition Survey (YITS) is a biennial and nationally representative longitudinal survey, developed and conducted jointly by Statistics Canada and Human Resources and Skills Development Canada (HRSDC). The YITS follows up young Canadians and provides information on their educational trajectories and employment experiences. It gives detailed information on educational and labor market pathways and on aspects influencing these pathways. Two target populations were surveyed: a

cohort of students who were 15 years old on December 31, 1999 (Cohort A) and a cohort of individuals who were 18 to 20 years old on December 31, 1999 (cohort B).

We firstly use the data provided by cohort A. The YITS has several Cycles for cohort A: Cycle 1 (1999), Cycle 2 (2000-2001), Cycle 3 (2002-2003), Cycle 4 (2004-2005), Cycle 5 (2006-2007), and Cycle 6 (2008-2009). Comparability across the cycles survey is possible. The first cycle (Cycle 1) was conducted in April 2000 to collect information on the year 1999. The questionnaires used in the following cycles were used to collect information over two-year periods. In 2002, Cycle 2 collected information on the years 2000 and 2001. In 2004, Cycle 3 collected information on the years 2002 and 2003. In 2006, information on the years 2004 and 2005 was collected during Cycle 4. Cycle 5 collected in 2008 information on the years 2006 and 2007. And finally in 2010, Cycle 6 collected information on the years 2008 and 2009. This makes a period of 10 years between Cycle 1 and Cycle 6 where young Canadians are being followed up. The YITS began with 29330 respondents in cycle 1. The number had fallen to 26880, 22682, 18843, 14751, and 11126 in cycles 2, 3, 4, 5 and 6 respectively. Cohort A also participated in the OECD's Program for International Student Assessment (PISA)[1]. A reading test was administered to the entire sample, a mathematics test to one half of the sample and a science test to the other half.

Four main variables are central for our analysis namely post-secondary education interruption status, level of education, remuneration and tenure at work. Using all available information from both previous and current cycles of the YITS, we establish respondents' post-secondary education interruption status as either a Continuer, a Leaver or a Temporary interrupter. Continuers are individuals who never interrupted their post-secondary schooling before graduation, Leavers interrupted their post-secondary schooling and had not returned to schooling. Temporary interrupters interrupted their post-secondary schooling and subsequently returned to schooling. These definitions are directly related to the YITS follow-up periods. In this study, schooling discontinuity is defined as any break or leave of absence apart from summer break or normal school holidays taken during a degree and causing the delay of its completion. Our definition excludes out-of-school spells taken between two degrees and degree-related gap years required by certain educational programs. Note that when some respondents have undertaken more than one program simultaneously, we retained the lengthiest and most recent one. We characterized levels of education into four categories : Post-secondary without certificate, Private business or training school diploma, College or Cegep and University. We retained as remuneration at work, the most recent hourly wage paid to the individual prior for each cycle.[2] If more than one job was held, the hourly wage variable refers to the job in which the individual spent most of his time. Tenure is the total number of relevant job experience in years. We exclude years of employment when the individual is below 16.[3]

[1]The OECD Programme for International Student Assessment (PISA) is a collaborative effort undertaken by all member countries and a number of non-member partner countries to measure how well students, at age 15, are prepared to meet the challenges they may encounter in future life. Age 15 is chosen because at this age, in most OECD countries, students are approaching the end of compulsory schooling, and so, some measure of the knowledge, skills and attitudes accumulated over approximately ten years of education is gained from an assessment at this time. The PISA assessment takes a broad approach to assessing knowledge, skills and attitudes that reflect current changes in curricula, moving beyond the school-based approach towards the use of knowledge in everyday tasks and challenges. The skills acquired reflect the ability of students to continue learning throughout their lives by applying what they learn in school to non-school environments, evaluating their choices and making decisions (OECD, 2003).

[2]For each Cycle, the YITS provides two hourly paid wages : a start job hourly wage and an end job hourly wage. The start job hourly wage refers to hourly wage paid to the worker when he first started working at a given job. The end job hourly wage is the most recent hourly wage paid to the worker prior to the interview. Retaining the most recent hourly wage enables to analyze wage growth in our study.

[3]Work experience acquired at the age below 16 is not considered to account for compulsory schooling and minimum legal working

4 Descriptive analysis

In this section, we present summary statistics on the post-secondary education status and hourly wages derived from the survey.

Out of 26880 respondents in Cycle 2, 3.74% (1007) had a post-secondary education. This percentage rises to 50.43% (11439 out of 22,682) and 65.68% (12377 out of 18843) respectively in Cycle 3 and Cycle 4. This percentage increases slightly to 65.85% (9714 out 14,751) in Cycle 5 and is about 54.39% (6048 out 11,126) in Cycle 6. The observed variation in the percentage of respondents having a post-secondary education is explained by new entries in post-secondary education as time elapses but also by attrition from one cycle to another. In a balanced panel where we retain only respondents who participated in all the survey cycles, this percentage will be non-decreasing. A balanced panel will, however, imply losing information.

Focusing on a post-secondary education, we observe a steady decline in the percentage of Continuers from about 96.32% in Cycle 1 (2000-2001) reaching 49.58% in Cycle 6 (2008-2009). Inversely the percentages of Leavers and Temporary Interrupters follow rather a positive trend, increasing from 1.79% and 1.89% in Cycle 1 (2000-2001) to 33.71% and 17.23% respectively in Cycle 6 (2008-2009). Indeed, in Cycle 2, respondents of Cohort A are aged 16-17 and just started post-secondary education which explains the huge percentage of Continuers (96.32%) and low percentages of Leavers (1.79%) and Temporary Interrupters (1.89%). At this time, respondents are very young and at their early stage of decision-making in regard to their educational pathways. But as time elapses, decisions are made and we observe dynamics in schooling with episodes of interruptions and re-enrollments consistent with previous studies.[4] Thus, the percentage of Continuers decreases and that of Leavers and Temporary interrupters increase with time as depicted on Figure 1.

Table 1 presents summary statistics on nominal and deflated hourly wage. We deflate using the average Consumer Price Index (CPI) of the period 2000-2001. In Cycle 2, average hourly wages of Continuers, Leavers and Temporary Interrupters are quite similar. They are respectively about C$7.66, C$7.25 and C$7.80.[5] Figure 2 depicts the evolution of these wages in subsequent cycles. Average deflated hourly wage of Continuers evolves from C$7.66 in cycle 1 to C$16.27 in cycle 6. That of Temporary interrupters follows a faster pace from C$7.25 in cycle 1 to C$17.51 to cycle 6. The pace of Leavers is the slowest from C$7.80 in cycle 1 to C$15.32 to cycle 6.

Figure 3 depicts the evolution of average tenure. In cycle 2, average tenure for both non-interrupters (Continuers) and interrupters (Leavers and Temporary interrupters) is less than 5 months. It increases to reach 21 months (1.76 years), 27 months (2.28 years) and 28 months (2.31 years) for Continuers, Leavers and Temporary interrupters.

age regulations. Indeed below 16, youth should be primarily at school and not work. Thus any work experience acquired during that period is discarded. Moreover Light (1998) also considered 16 years as the earliest career starting age.

[4]Note that the post-secondary education status in each cycle is not necessarily final.

[5]In general earnings of young adults are much lower than earnings across the entire age range of individuals in the labor market. Moreover at early cycles, these wages may also include significant part-time wages.

Figure 1: Percentage of post-secondary education status, YITS Cohort A

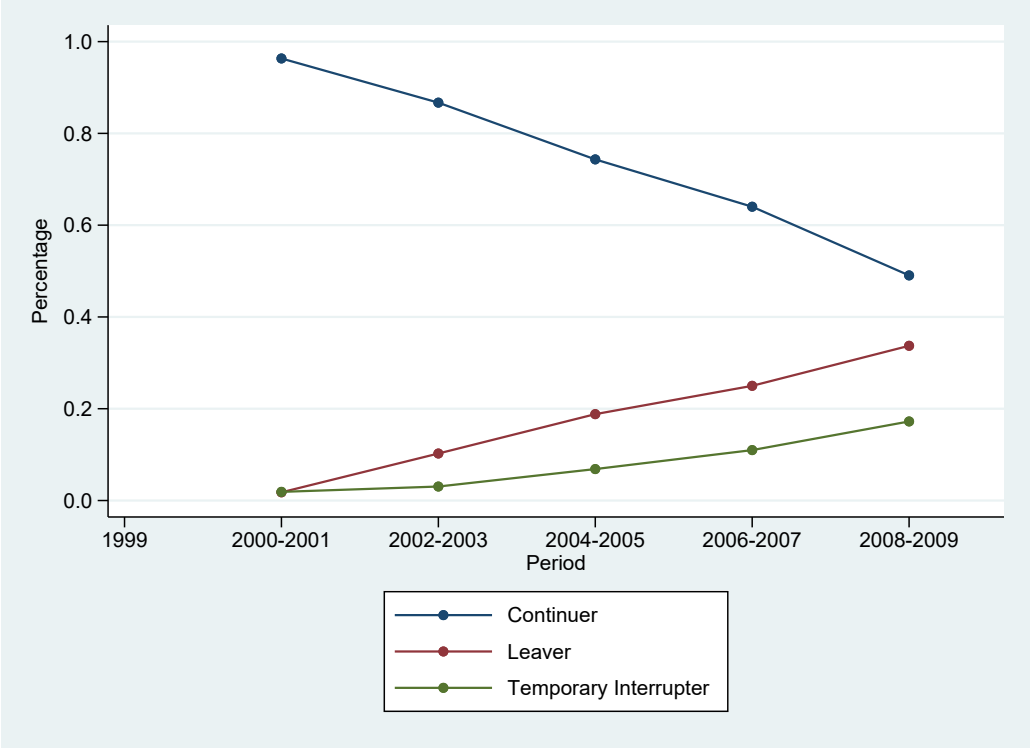


Table 1: Summary statistics on average nominal and deflated hourly wage, YITS Cohort A

		Nominal hourly wage				Deflated hourly wage (IPC Base=2000-2001)			
Period	Interruption Status	Average	Median	Sd	Observations	Average	Median	Sd	Observations
Cycle 2 2000-2001	Continuer	7.66	7.10	2.24	970	7.66	7.10	2.24	970
	Leaver	7.80	7.13	1.46	18	7.80	7.13	1.46	18
	Temporary Interrupter	7.25	7.00	1.30	19	7.25	7.00	1.30	19
Cycle 3 2002-2003	Continuer	8.60	8.00	3.07	9918	8.48	7.89	3.03	9918
	Leaver	8.88	8.00	3.12	1172	8.76	7.89	3.08	1172
	Temporary Interrupter	8.52	8.00	3.00	349	8.40	7.89	2.96	349
Cycle 4 2004-2005	Continuer	10.92	10.00	4.61	9200	10.31	9.45	4.35	9200
	Leaver	10.78	9.50	5.52	2329	10.18	8.97	5.22	2329
	Temporary Interrupter	11.22	10.00	4.44	848	10.60	9.45	4.20	848
Cycle 5 2006-2007	Continuer	14.74	13.00	7.69	6219	13.37	11.79	6.97	6219
	Leaver	14.36	12.50	9.79	2428	13.02	11.33	8.88	2428
	Temporary Interrupter	15.12	13.75	7.58	1067	13.71	12.47	6.87	1067
Cycle 6 2008-2009	Continuer	18.59	17.25	8.29	2967	16.27	15.10	7.26	2967
	Leaver	17.50	16.00	7.56	2039	15.32	14.00	6.62	2039
	Temporary Interrupter	20.00	18.75	8.49	1042	17.51	16.41	7.43	1042

Table 2: Tenure (in years), YITS Cohort A

Period	Interruption Status	Average	Median	Sd	Observations
Cycle 2 2000-2001	Continuer	0.34	0.25	0.21	970
	Leaver	0.29	0.21	0.22	18
	Temporary Interrupter	0.34	0.33	0.19	19
Cycle 3 2002-2003	Continuer	0.87	0.50	0.77	9916
	Leaver	0.77	0.50	0.70	1172
	Temporary Interrupter	0.82	0.50	0.70	349
Cycle 4 2004-2005	Continuer	1.15	0.67	1.11	9199
	Leaver	1.22	0.92	1.07	2328
	Temporary Interrupter	1.25	0.92	1.09	847
Cycle 5 2006-2007	Continuer	1.34	0.75	1.39	6219
	Leaver	1.63	1.25	1.44	2428
	Temporary Interrupter	1.61	1.25	1.41	1067
Cycle 6 2008-2009	Continuer	1.76	1.33	1.59	2966
	Leaver	2.28	1.92	1.81	2039
	Temporary Interrupter	2.31	1.83	1.81	1043

Figure 2: Average nominal and deflated hourly wage, YITS Cohort A

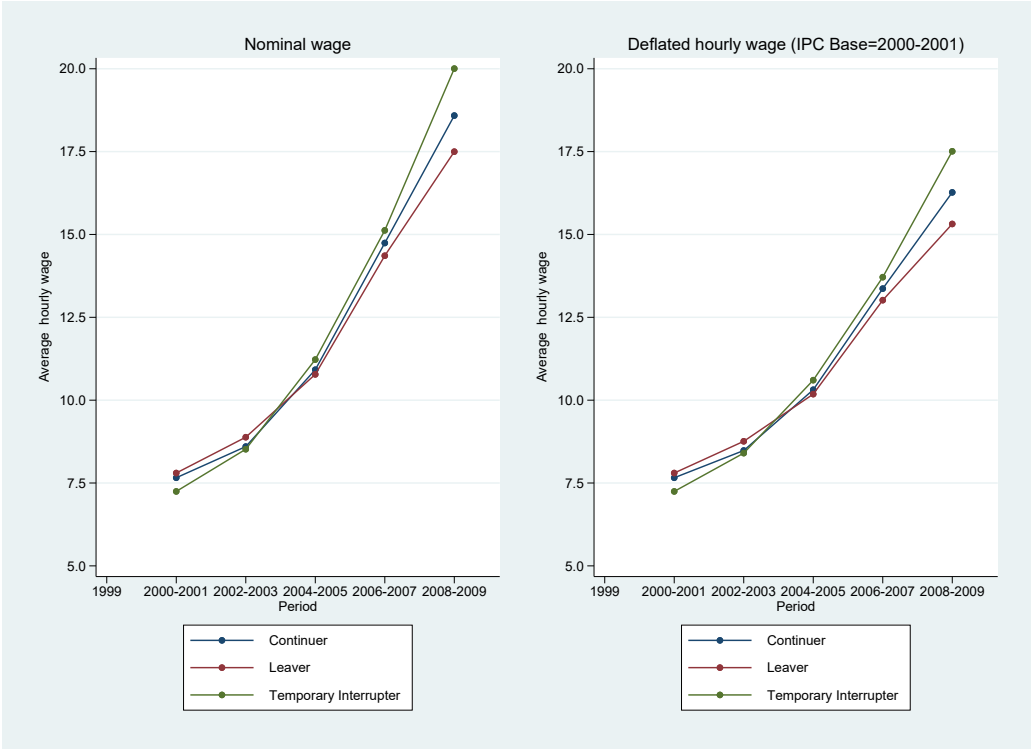
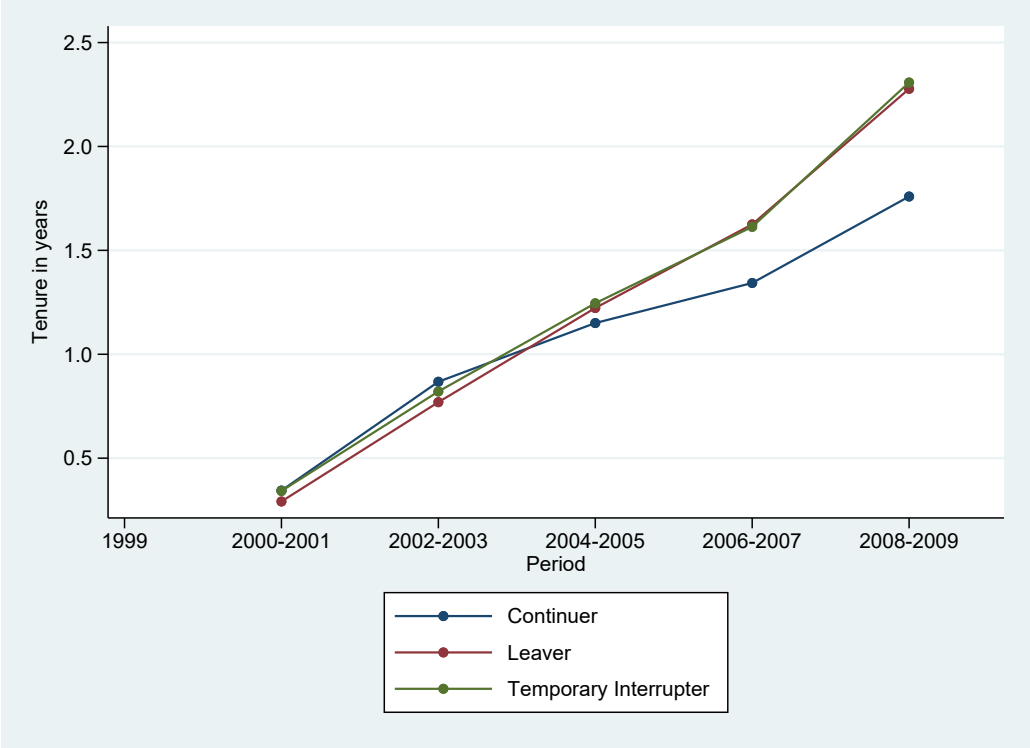


Figure 3: Average Tenure (in years), YITS Cohort A



5 Estimation of the wage gap

We develop estimation strategies in this section to estimate the impact of both temporary and permanent interruption on wages and consequently measure wage gaps across post-secondary education interruption status (Continuers, Leavers and Temporary interrupters).

5.1 Econometric specification

We adopt an augmented mincer wage equation where the logarithm of the individual's hourly wage at a given period is expressed as an additive function of his post-secondary education status (Continuer, Leaver or Temporary Interrupter), his level of education, a quadratic term of his tenure at work and some control variables.[6] Our analysis focuses on individuals who have a post-secondary education either completed or not. Years of schooling are replaced by levels of education as provided in the YITS data. Using levels of education allows for maximum flexibility in estimation. This specification has been adopted by several authors (Card and Krueger, 1992; Light, 1995b; Edin et al., 1995).[7]

Without appropriate econometric strategies, the estimation of the mincer equation suffers from endogeneity issues. The education level variable is usually correlated to the unobserved components of the wage equation.[8]

[6]Standard mincer wage equation expresses the logarithm of the individual hourly wage at a given period as an additive function of a linear education term and a quadratic experience term. In our study, this equation is augmented by including notably the post-secondary education of the individual (Continuer, Leaver or Temporary Interrupter).

[7]In the US, many analysts have argued that credentials (such as a high school diploma or college degree) matter more than years of schooling per se. This hypothesis has come to be known as the "sheepskin effect" - the existence of wage premiums for fulfilling the final years of elementary school, high school, or college (Card, 1999).

[8]Papers focusing on returns to education discuss extensively the endogeneity of the education variable (for example Card, 1999, 2001).

Moreover the post-secondary education interruption status (fundamental variable of our analysis) is also endogenous as the decision to interrupt and/or to return to school is generally the result of individual choice rather than random assignment. Indeed post-secondary education status and education level are likely to be correlated to unobserved variables such as ability, tastes, motivation, parental support which in turn influence wages.[9] The econometric strategies we adopt must account for the fact that the schooling variables and other regressors are likely to be correlated with the error term of the wage equation.

5.1.1 Standard OLS and endogeneity issues

Our mincer augmented wage equation is specified as :

$$\log w_{it} = \alpha_0 + \alpha_1 L_{it} + \alpha_2 T_{it} + \sum_k \gamma_k Ed_{k,it} + \mu_1 Tenure_{it} + \mu_2 Tenure_{it}^2 + \phi_1 Tenure_{it} \times L_{it} + \phi_2 Tenure_{it} \times T_{it} + \theta_1 Tenure_{it}^2 \times L_{it} + \theta_2 Tenure_{it}^2 \times T_{it} + \beta X_{it} + \epsilon_{it} \quad (1)$$

where

- $\log w_{it}$ is the logarithm of the CPI-deflated hourly wage received by individual i at time t ;
- L_{it} is a dummy variable equal to 1 if the individual is a Leaver at time t and 0 otherwise ;
- T_{it} is a dummy variable equal to 1 if the individual is a Temporary Interrupter at time t and 0 otherwise [10];
- $Ed_{k,it}$ are dummy variables capturing education levels attained at time t by individual i. We retain four categories education levels : Post-secondary without certificate, Private business or training school diploma, College or Cegep and University. Post-secondary without certificate is used as the reference level omitted for estimation purposes.
- $Tenure_{it}$ is the amount of tenure acquired by individual i at time t;
- $\phi's$ are coefficients on the interaction terms between post-secondary education status (L_{it} and T_{it}) and tenure;
- $\theta's$ are coefficients on the interaction terms between post-secondary education status (L_{it} and T_{it}) and square of tenure;
- X_{it} is a set of control variables that includes individual's gender, marital status, a dummy variable indicating whether the individual worked less than 30 hours per week, PISA test score in reading and province of work, number of siblings and presence of both parents at home at age 15;

[9] Previous Canadian research reveals that "lack of interest" comes out among the most reported reasons for discontinuing studies, implying that motivation plays an important role with respect to the continuity of post-secondary education (Finnie and Qiu, 2008). This same motivation may also be an element affecting wages. Other reasons include lack of career planning or academic difficulties. The latter is related with ability and therefore also affects wages. The endogeniety of the education level variable is sufficiently developed in the returns to education literature.

[10] Notice that the Temporary interrupter state is an absorbing state. Once the individual is a Temporary interrupter at given period, he is stays a Temporary interrupter for subsequent periods. The Continuer and Leaver state are on the contrary non-absorbing states.

– ϵ_{it} is the error term.

The estimation of equation (1) by OLS poses several econometric issues. Indeed , individual effects that cannot be measured such as ability, tastes, motivation, parental support cause bias in the estimates because they are correlated with the education covariates. Among these potential sources of endogeneity, ability bias appears to be the most important (Griliches, 1977; Blackburn and Neumark, 1993; Belzil and Hansen, 2002, 2003). Ability bias is usually discussed as a problem of omitted variables (see Griliches, 1977; Chamberlain and Griliches, 1975). Thus, including the missing ability variable and, except for problems of measurement error, there will be no bias.

The use of test scores as control variables (or proxies thereof) measuring unobserved ability is not uncommon (Griliches, 1977; Willis and Rosen, 1979; Blackburn and Neumark, 1993; Grogger and Eide, 1995; Murnane et al., 1995; Light, 2001; Belzil and Hansen, 2003). The rationale is that test scores will absorb sample heterogeneity in individual ability and thus reduce the endogeneity problem. Moreover in some sense, test scores can also serve as proxies to account for parental and school investments. Drewes (2010) shows that family background factors are important determinants of PISA test scores. Hence, PISA test scores can help to control for two levels of endogeneity : ability and parental investment which influence both labor outcomes and education attainment. In the YITS we have PISA test scores for reading, mathematics and science. A reading test was administered to the entire sample, a mathematics test to one half of the sample, and a science test to the other half. It would be interesting to include all these test scores as controls but doing so will reduce considerably our sample size. For this reason, we use solely the reading score as in Hansen and Liu (2013a).

Note, however, that both education covariates and observed ability will continue to be correlated with unobserved factors if test scores are imperfect proxies for the true ability affecting schooling decisions.

5.1.2 Instrumental variable regressions

Instrumental variables (IV) regressions are advocated to yield appropriate estimates in the presence of endogeneity (Angrist and Keueger, 1991; Angrist et al., 1996; Card, 2001). We must find instruments that are strongly correlated with the endogenous variables and that satisfy the exclusion restriction (i.e., having no direct effect on wages).

A substantial literature has been devoted to the estimation of wage equation where education choices are suitably instrumented out. Many studies are reviewed in Card (1999, 2001). Some authors exploit institutional features or policy changes while others rely on the identification of exogenous influences on schooling decisions such as the season of birth (Angrist and Keueger, 1991), military service lotteries (Angrist and Krueger, 1992), geographical location or college proximity (Card, 1993). Other proposed generated internal instruments (Lewbel, 2012; Klein and Vella, 2010) when external instruments are absent or limited in number.[11] Instrumental variable regressions are not, however, exempt of drawbacks. Weak instruments (i.e. instruments although uncorrelated with wages are weakly correlated with the endogenous covariates) and invalid instruments (i.e. instruments that are correlated both with wages and endogenous covariates) may be worse than no instruments at all (Bound et al., 1993).

Confronted with the difficulty to find sufficient valid instruments for all our endogenous education covariates,

[11] Some authors resorted to these internal instruments (Sabia, 2007; Kelly and Markowitz, 2007; Emran and Hou, 2013; Millimet and Roy, 2016; Fortin and Ragued, 2017).

the panel structure data offers us interesting econometric alternatives.

5.1.3 Random Effects estimation

A panel structured data offers an advantage over a cross-sectional one as data on the same individual is observed at several points in time. This enables us to control for the individual's unobserved time-invariant characteristics. It thus offers the opportunity to handle endogeneity without resorting to external instruments if the source of endogeneity is an unobserved time-invariant individual characteristics such as ability in our case that affects both wages and the education covariates.

In equation (1), let us now consider the error term ϵ_{it} as being composed of a time-invariant personal effect λ_i plus white noise ξ_{it}. The resulting equation becomes :

$$\begin{aligned}\log w_{it} = \alpha_0 + \alpha_1 L_{it} + \alpha_2 T_{it} + \sum_k \gamma_k Ed_{k,it} + \mu_1 Tenure_{it} + \mu_2 Tenure_{it}^2 + \phi_1 Tenure_{it} \times L_{it} \\ + \phi_2 Tenure_{it} \times T_{it} + \theta_1 Tenure_{it}^2 \times L_{it} + \theta_2 Tenure_{it}^2 \times T_{it} + \beta X_{it} + \lambda_i + \xi_{it}\end{aligned} \tag{2}$$

Equation (2) is a Random effects model if the individual-specific effect λ_i is uncorrelated with the other regressors. In our study, it is, however, unlikely to assume that α_i is uncorrelated with the regressors. Indeed education attainment, schooling decisions in terms of interruption and re-enrollment are generally affected by unobserved, time-invariant, personal characteristics such as innate ability (see, for example, Griliches, 1977; Light 1995b). In this situation, the Random effects model will generally produce biased estimates.

5.1.4 Fixed Effects estimation

The Fixed effects model allows the time-invariant individual effects λ_i in equation (2) to be correlated with the other regressors. The model can be estimated by expressing the variables as deviation from their individual-specific means. This helps to purge out the effects of the time-invariant individual characteristics λ_i. The resulting estimates is then unbiased by the assumed correlation between the regressors and λ_i. Time-invariant regressors cannot, however, be identified under a Fixed effects estimation. This constitutes its main limitation. This may not matter much in our study as the panel of our study is observed over a quite long period (1999-2009) allowing key variables to vary with time.

5.1.5 Hausman & Taylor estimation

An interesting alternative to the Fixed effects model is the Hausman and Taylor (1981) model. This approach controls for both endogeneity bias caused by time-invariant unobservables and allows the identification of time-constant regressors. It can be seen as an intermediate approach between random effects and fixed effects models. The random effects models treat all variables as exogenous, and fixed effects assume all variables are endogenous. Hausman and Taylor (1981) instead choose some variables to be exogenous and others as endogenous. They then exploit internal instruments in a way that allows them to both deal with endogenous covariates and identify the time-invariant regressors.

In the Hausman and Taylor method, λ_i is assumed to be distributed independently across individuals with mean zero and a constant variance σ_λ^2. The model is estimated via generalized least squares using instruments for the endogenous covariates that are correlated with λ_i. Exploiting the panel structure of the data, Hausman

and Taylor (1981) suggest using the deviations from individual means of each time-varying (endogenous as well as exogenous) plus the means of each exogenous variable as instruments for the endogenous covariates. These internal instruments are uncorrelated with λ_i by construction. The authors also include a weighting procedure into their approach to ensure efficient estimates. The overall Hausman and Taylor method is thus known as Efficient Generalized Instrumental Variables, and it yields consistent and asymptotically efficient estimators (Wooldridge, 2002). In our study, we treat all education related, job related and interaction covariates as endogenous when applying the Hausman and Taylor estimation.

Note that the panel estimation strategies we presented, implicitly assume that the residual ξ_{it} is not uncorrelated with the regressors. Indeed as Light (1995b), we assume that the schooling decisions (education attainment, interruption and re-enrollment) appear to be correlated with time-invariant personal characteristics and not with transitory wage shocks. By holding this true and accounting for correlation between the education and job covariates of our mincer equation and time-invariant unobservables λ_i, panel econometric strategies enable to produce unbiased estimates.

5.1.6 Empirical results

Table 3 presents estimations results from our above discussed econometric techniques : OLS, Random effects, Fixed effects and Hausman-Taylor estimations. The OLS and Random effects are mainly presented for illustrative and comparative purposes. For the Hausman-Taylor estimator to be consistent, it is necessary to argue that our exogenous variables are uncorrelated with the time-invariant individual characteristics λ_i. We accept the null hypothesis that our assigned exogenous variables are uncorrelated with λ_i by running a Sargan-Hansen test (p-value>10%). Thus our regressors are correctly assigned to the endogenous and exogenous category - indispensable for a consistent Hausman-Taylor estimation.

The OLS and Random Effects suggest a slight wage penalty related to school interruption either it be permanent or temporary. Indeed the coefficient $\alpha's$ on the dummy variables Leavers and Temporary Interrupter are negative and statistical significant though very small. These estimates are, however, potentially biased though we control with PISA reading score as an ability measure. Focusing on the fixed effects and Hausman-Taylor estimations which are the most convincing because dealing with possible correlation between covariates and time-invariant individual characteristics, we find that this wage penalty is marginal -less than 3%. For Temporary interrupters, it appears even negligible - less than 1%. We can't estimate precisely with the Fixed effects and Hausman-Taylor models, though the value is negative. Our results are consistent with the literature that found little evidence of the existence of wage penalty associated to school interruption (Griliches, 1980; Marcus, 1984).

The education level variables are significant and suggest that wages increase when schooling level increases in conformity with the literature. Fixed effects and Hausman-Taylor yield smaller estimates than OLS and random effects. The OLS and random effects appears thus to be upward biased regarding education level variables as developed in the literature. Earning a post-secondary diploma increases wages and the intensity of this increase amplifies with the level of education. University graduates earn more, followed by College and Cegep graduates, then private business and training schools. Those with post-secondary without certificate earn on average less.

All models agree that wages increase with tenure (positive and statistical significant μ_1). This growth is concave as illustrated by the negative and statistical significant coefficient μ_2. The wage growth of Temporary

Interrupters is the fastest. Indeed the coefficient ϕ_2 on the interaction between Temporary Interrupter and tenure is positive and statistical significant for all models.

Though not of primary interest to this study, our background and control variables are significant and consistent with literature. Males earn more, full-time job is well paid than a part-time job etc.

Table 3: Estimation of the wage equation, YITS Cohort A

	OLS	Random Effects	Fixed Effects	Hausman-Taylor
Interruption Status (Ref: Continuer)				
Leaver (α_1)	-0.0315***	-0.0262***	-0.0167	-0.0171
	(0.0088)	(0.0089)	(0.0138)	(0.0138)
Temporary Interrupter (α_2)	-0.0238*	-0.0204	-0.0073	-0.0072
	(0.0136)	(0.0133)	(0.0180)	(0.0180)
Education level				
(Ref: Post-secondary without certificate)				
Private business or training school	0.0242**	0.0242*	0.011	0.0161
	(0.0123)	(0.0131)	(0.0205)	(0.0206)
College or Cegep	0.0855***	0.0856***	0.0649***	0.0664***
	(0.0055)	(0.0057)	(0.0079)	(0.0079)
University	0.1323***	0.1265***	0.0954***	0.0965***
	(0.0075)	(0.0075)	(0.0089)	(0.0089)
Tenure (μ_1)	0.0829***	0.0788***	0.0669***	0.0666***
	(0.0050)	(0.0049)	(0.0061)	(0.0061)
Leaver X Tenure (ϕ_1)	0.0151*	0.0115	0.002	0.0018
	(0.0090)	(0.0086)	(0.0097)	(0.0097)
Temporary Interrupter X Tenure (ϕ_2)	0.0343**	0.0342***	0.0327**	0.0326**
	(0.0137)	(0.0128)	(0.0145)	(0.0144)
Tenure2 (μ_2)	-0.0111***	-0.0113***	-0.0121***	-0.0122***
	(0.0010)	(0.0010)	(0.0013)	(0.0013)
Leaver X Tenure2 (θ_1)	0.0013	0.0014	0.0021	0.0022
	(0.0017)	(0.0016)	(0.0017)	(0.0017)
Temporary Interrupter X Tenure2 (θ_2)	-0.001	-0.0017	-0.0028	-0.0027
	(0.0024)	(0.0022)	(0.0025)	(0.0024)
Male	0.1038***	0.1061***		0.1086***
	(0.0039)	(0.0045)		(0.0047)
Matrimonial Status (Ref : Single)				
Married or Living together	0.0511***	0.0521***	0.0569***	0.0579***
	(0.0061)	(0.0064)	(0.0081)	(0.0081)
Separated/Divorced/Widowed	-0.0694*	-0.0464	0.049	0.0473
	(0.0405)	(0.0415)	(0.0468)	(0.0467)
Worked less than 30 hours=1	-0.1091***	-0.0993***	-0.0710***	-0.0715***
	(0.0047)	(0.0051)	(0.0070)	(0.0070)
Score in reading	0.0000	0.0000		0.0001*
	(0.0000)	(0.0000)		(0.0000)
Presence of both Parents	0.0292***	0.0306***		0.0349***
	(0.0056)	(0.0066)		(0.0068)
Number of siblings	-0.0030*	-0.0029		-0.0029
	(0.0016)	(0.0019)		(0.0020)
Constant	1.7416***	1.7187***	1.7139***	1.6668***
	(0.0192)	(0.0213)	(0.0267)	(0.0264)
Region specific effect	yes	yes	yes	yes
Period specific effect	yes	yes	yes	yes
Observations	35767	35767	35767	35767
Sargan-Hansen (Statistic)				16.1917
Sargan-Hansen (P-Value)				0.1826

Panel-robust standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Our panel estimation strategy relied on the fact that individuals are observed at multiple times. In previous estimations, not all individuals are observed over the whole period of the YITS. For robustness check, we now consider a restricted balanced version of our data where we focused on individuals that were followed over the whole period of the survey. Table 4 contains results of estimations on this restricted balanced version of data. The results are similar with those from the non-restricted unbalanced data.

Table 4: Estimation of the wage equation, YITS Cohort A (Restricted panel)

	OLS	Random Effects	Fixed Effects	Hausman-Taylor
Interruption Status (Ref: Continuer)				
Leaver (α_1)	-0.0330***	-0.0280**	-0.0173	-0.0179
	(0.0108)	(0.0110)	(0.0161)	(0.0161)
Temporary Interrupter (α_2)	-0.0277*	-0.0212	-0.0013	-0.0017
	(0.0165)	(0.0162)	(0.0207)	(0.0206)
Education level				
(Ref: Post-secondary without certificate)				
Private business or training school	0.0334**	0.0321*	0.02	0.027
	(0.0152)	(0.0164)	(0.0242)	(0.0243)
College or Cegep	0.0833***	0.0827***	0.0636***	0.0643***
	(0.0066)	(0.0069)	(0.0092)	(0.0091)
University	0.1424***	0.1347***	0.1037***	0.1043***
	(0.0083)	(0.0083)	(0.0098)	(0.0098)
Tenure (μ_1)	0.0970***	0.0906***	0.0767***	0.0764***
	(0.0059)	(0.0059)	(0.0069)	(0.0069)
Leaver X Tenure (ϕ_1)	0.0109	0.0073	-0.0001	-0.0004
	(0.0104)	(0.0098)	(0.0108)	(0.0107)
Temporary Interrupter X Tenure (ϕ_2)	0.0404**	0.0383***	0.0320**	0.0322**
	(0.0158)	(0.0146)	(0.0159)	(0.0159)
Tenure2 (μ_2)	-0.0128***	-0.0130***	-0.0133***	-0.0133***
	(0.0012)	(0.0012)	(0.0014)	(0.0014)
Leaver X Tenure2 (θ_1)	0.0023	0.0024	0.0026	0.0026
	(0.0018)	(0.0017)	(0.0019)	(0.0019)
Temporary Interrupter X Tenure2 (θ_2)	-0.0016	-0.0021	-0.0024	-0.0024
	(0.0027)	(0.0024)	(0.0026)	(0.0026)
Male	0.1032***	0.1066***		0.1087***
	(0.0047)	(0.0058)		(0.0060)
Matrimonial Status (Ref : Single)				
Married or Living together	0.0564***	0.0575***	0.0588***	0.0598***
	(0.0070)	(0.0074)	(0.0089)	(0.0089)
Separated/Divorced/Widowed	-0.0720*	-0.0368	0.0716	0.0707
	(0.0416)	(0.0426)	(0.0473)	(0.0474)
Worked less than 30 hours=1	-0.1192***	-0.1050***	-0.0729***	-0.0737***
	(0.0059)	(0.0065)	(0.0082)	(0.0082)
Score in reading	0.0000	0.0001		0.0001*
	(0.0000)	(0.0000)		(0.0000)
Presence of both Parents	0.0280***	0.0304***		0.0350***
	(0.0070)	(0.0087)		(0.0090)
Number of siblings	-0.0044**	-0.0044*		-0.0047*
	(0.0021)	(0.0025)		(0.0026)
Constant	1.7428***	1.7126***	1.7107***	1.6692***
	(0.0245)	(0.0279)	(0.0318)	(0.0351)
Region specific effect	yes	yes	yes	yes
Period specific effect	yes	yes	yes	yes
Observations	25062	25062	25062	25062
Sargan-Hansen (Statistic)				15.7039
Sargan-Hansen (P-Value)				0.2052

Panel-robust standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

5.2 Wage gap growth analysis

One main result derived from previous estimations is that the coefficient (μ_1) on the interaction term between tenure and the Temporary Interrupter dummy variable is significant. This shows that the wage growths are different across post-secondary interruption status.

Figure 4 and Figure 5 predict expected average hourly wage in function of tenure for Cohort A and its restricted balanced version respectively. We observe that for both cases, the average wage of Temporary Interrupters evolves faster than those of their non-interrupter counterparts. This may be explained by the fact that Temporary Interrupters benefit from better market prospects during their interruption spell to tailor their education when they return to school. Indeed as advanced by Altonji (1993) , new information about preferences, abilities and/or market opportunities which compel individuals to alter or abort their studies, motivate them to re-enroll to tailor their education. The same also applies when individuals switch jobs and need new sets of skills required by their new occupations. Ferrer and Menendez (2014) advocate similar reasons to explain why college delayers earn significantly more than college non-delayers. Indeed Ferrer and Menendez (2014) suggest that delaying college to work full-time can increase subsequent wages by helping delayers learn about their abilities, aspirations and labor market before returning to school to earn a college degree. Light (2001) also suggests that students might decide to work in order to acquire marketable skills that are different than the skills gained through school. In addition to acquiring marketable skills, Interrupters are likely to gain a sense of responsibility and improve their job search and interpersonal skills, all of which may have a payoff in the labor market.

These arguments are further reinforced in YITS where majority of post-secondary interrupters were less likely to feel attached to their program. For instance, Lambert et al. (2004) examines the first two cycles of the YITS and found that the main reason for interrupting school is related to lack of program fit.

Figure 4: Estimation of the wage growth, YITS Cohort A

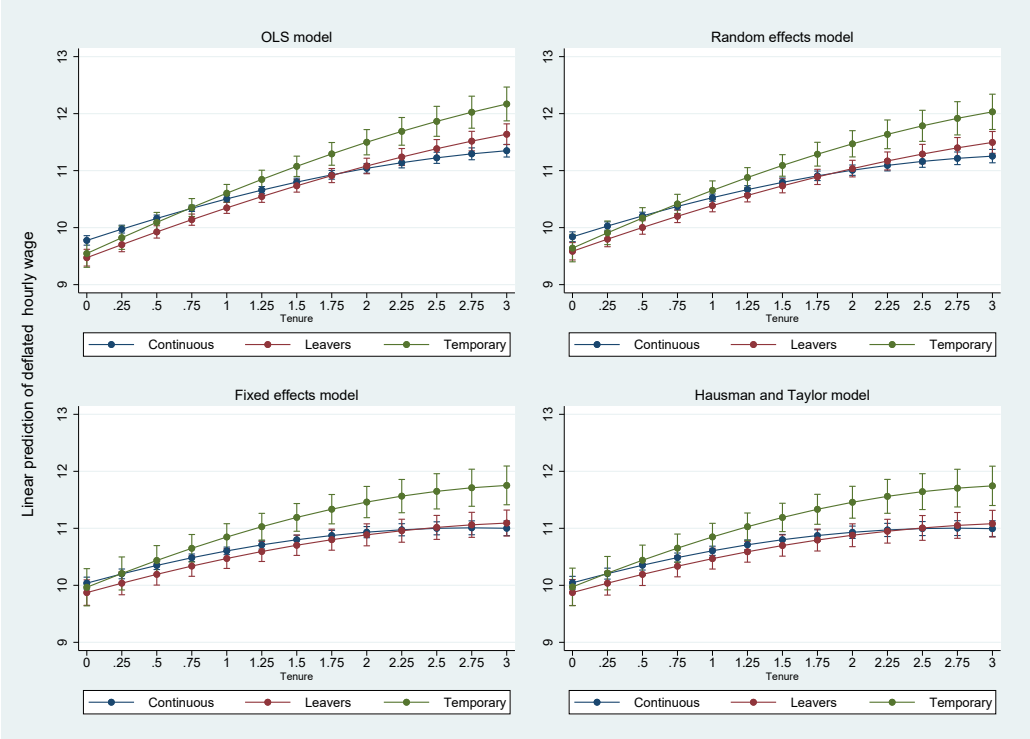
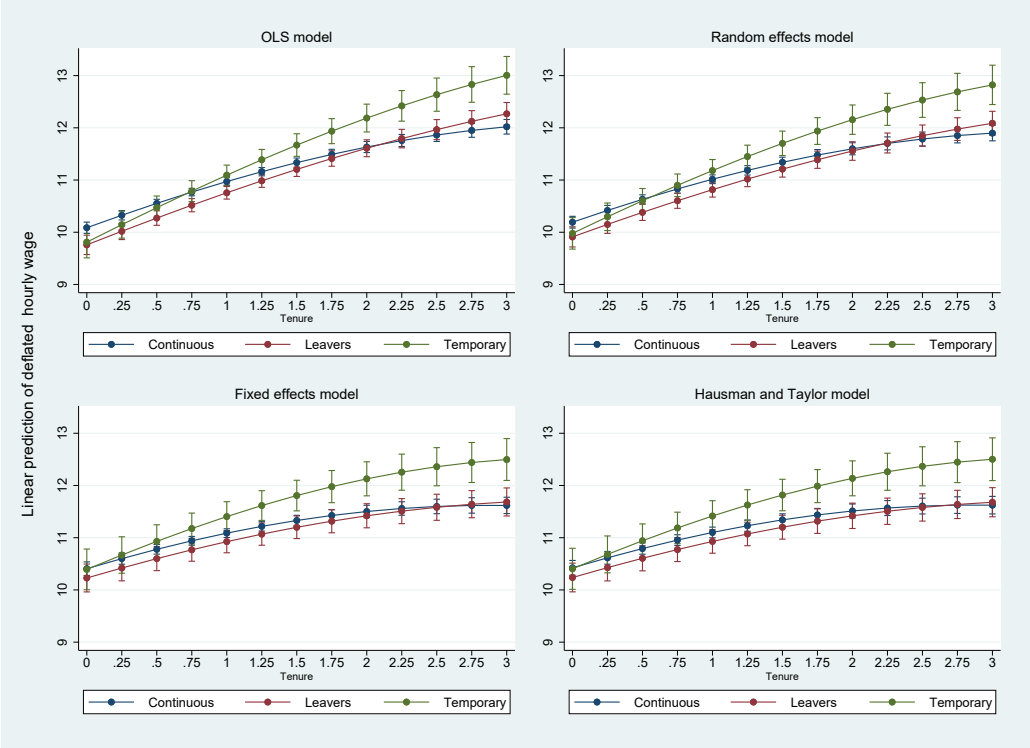


Figure 5: Estimation of the wage growth, YITS Cohort A (Restricted panel)



5.3 Analysis on an older but more heterogeneous population

There are two distinct cohorts surveyed in the YITS : Cohort A and Cohort B. Previous analysis was conducted on Cohort A. Cohort A offered the advantage of being observed for a total of 06 cycles (from 1999 to 2009) whereas cohort B was observed for a total of 05 cycles (from 1999 to 2007). Besides, Cohort A also contained reading test scores which served as controls in our regressions.[12] Cohort A is also homogeneous in the sense that all respondents are sampled based on participation in the education system and aged 15 at the beginning of the survey.

Inversely, Cohort B is rather heterogeneous - respondents are aged 18-20 years at the beginning of the survey- but offers an older population for the study. Moreover this population offers interesting features regarding labor participation. Indeed, Cohort B was selected from the Labor Force Survey (LFS). Respondents were representative of young Canadians aged 18-20 regardless of educational histories. For these reasons, analysis on Cohort B is also welcomed to have a complete of the impact of permanent and temporary interruption on wages despite heterogeneity in age and educational histories.[13]

Descriptive statistics on average hourly wage and tenure of Cohort B are sent to the Appendix. Figure 6 shows comparison between Cohort A and Cohort B in terms of post-secondary interruption status. Compared to Cohort A, the percentage of Leavers and Temporary Interrupters at the end of each cycle increases very rapidly in Cohort B. In the final cycle of Cohort B, the percentage of interruption both permanent and temporary amounted to 77.50% far above 50.94% in Cohort A. The Figure also shows that in Cohort B, the percentage of Temporary Interrupters appears higher than those leavers at each cycle. In Cohort A, it is rather the inverse -

[12] This cohort also participated in the survey of the International Program for the Monitoring of Learning students (PISA) which enabled to provide the PISA reading test score.

[13] Aged between 18 and 20 as of January 1, 2000, Cohort B respondents were not necessarily enrolled in an academic program when the survey began. The diversity of situations was therefore higher than was the case with Cohort A.

the percentage of leavers is rather higher. These differences are not very surprising as we take into account the relative older age of Cohort B and the diversity of respondent's educational histories. Indeed as respondents grow old, sufficient time is elapsed to observe dynamics in schooling decisions with episodes of interruptions and re-enrollments at early cycles. Figure 7 shows evolution of average hourly wage of the two Cohort A and B. Wages appear in general much higher in cohort B than in cohort A. With time, the disparity in wages by post-secondary interruption status at least for Leavers appear more pronounced in Cohort B than in Cohort A. Figure 8 shows as expected that Cohort B has a longer average tenure than Cohort A. At the final cycle of cohort B, average tenure is 2.19 years, 2.72 years and 2.74 years respectively for Continuers, Leavers and Temporary Interrupters. Corresponding numbers are 1.76 years, 2.28 years and 2.31 years for Continuers, Leavers and Temporary interrupters in Cohort A.

Figure 6: Percentage of post-secondary education status, YITS Cohort A vs Cohort B

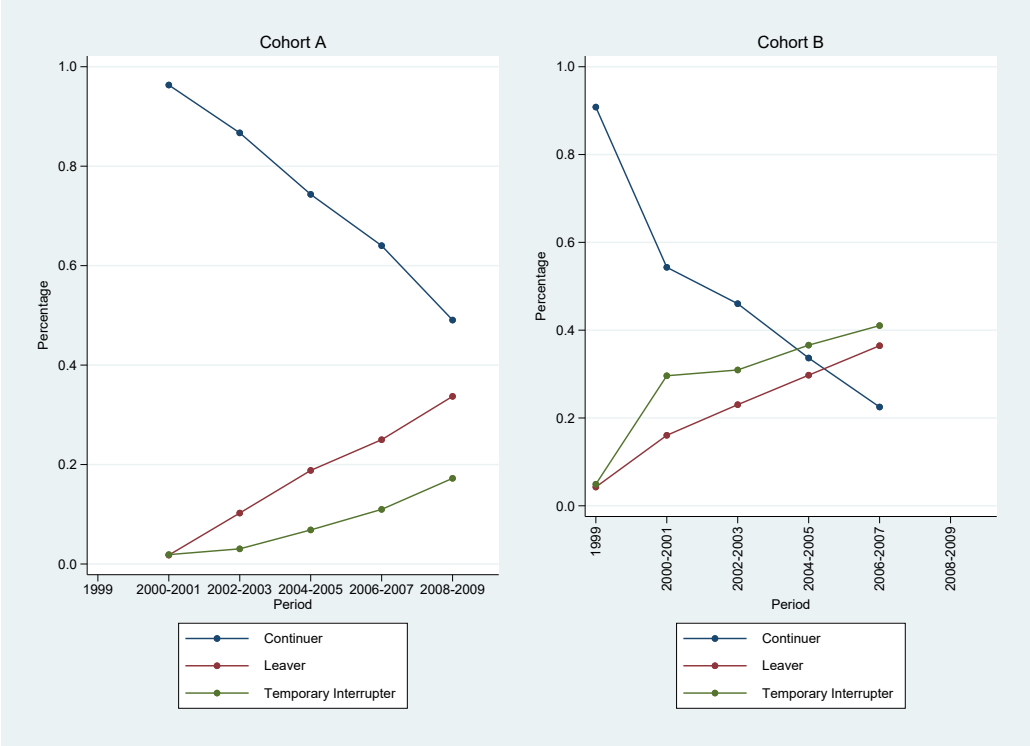


Figure 7: Average deflated hourly wage (IPC Base=2000-2001), YITS Cohort A vs Cohort B

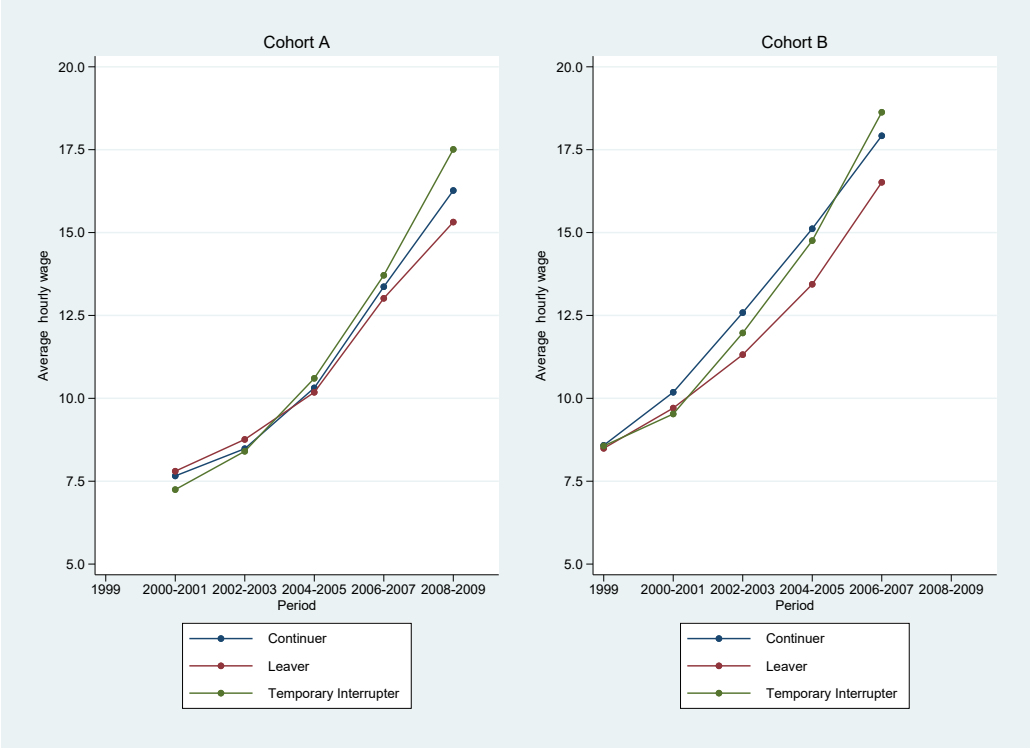
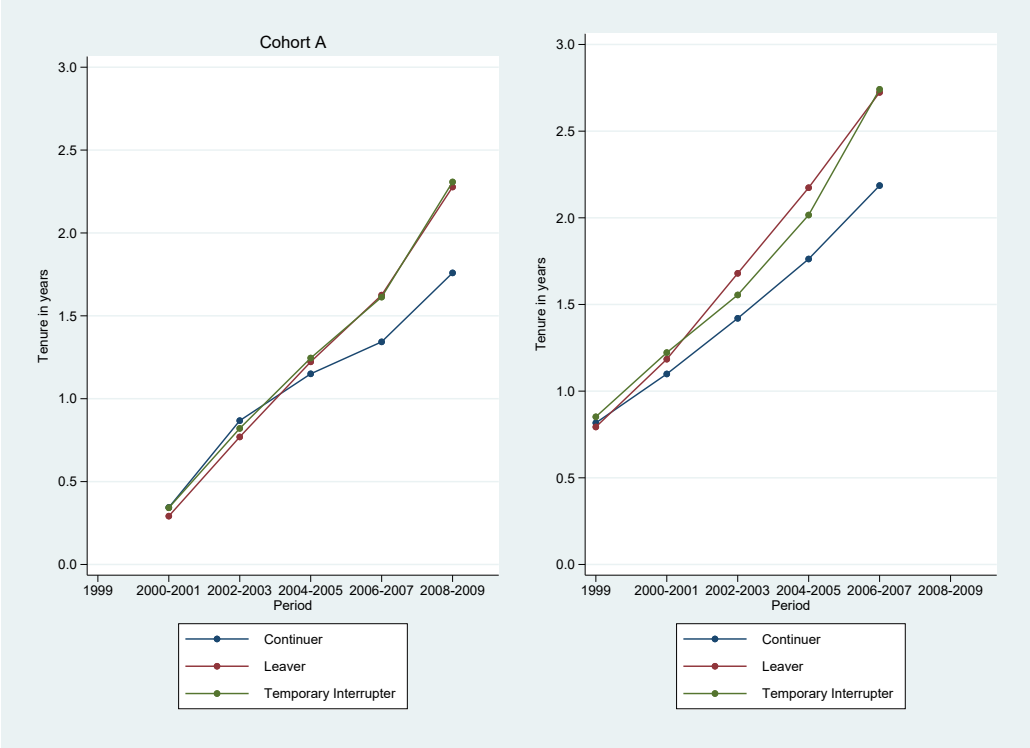


Figure 8: Average Tenure (in years), YITS Cohort A vs Cohort B



Estimations on Cohort B are given in Table 5. We consider the restricted balanced version as done in cohort A for the analysis. Note that compared to cohort A estimations, we don't have the PISA reading test score to account for as a control variable. We include respondent's age at the start of the survey as dummy variables to account for heterogeneity in age in Cohort B. We focus directly on the fixed effects and Hausman-Taylor

estimations. The OLS and random effects estimation are, however, given solely for reference purposes. We also run the Sargan-Hansen test of exogenous variables of the Hausman-Taylor model. Estimations are consistent with those from the cohort A in the previous section. The results suggest a wage penalty related to both temporary and permanent interruptions. However compared to cohort A, the coefficients α_1 and α_2 relating to these interruptions are more precisely estimated and the intensity of the wage gap is bigger in Cohort B. It is, however, still less than 5%.

As found in Cohort A, the wage growth of Temporary Interrupters evolves faster with the number of years of tenure. The coefficients ϕ_1 and ϕ_2 are positive, however, they are not precisely estimated except for the OLS and random effects estimates.

Table 5: Estimation of the wage equation, YITS Cohort B (Restricted panel)

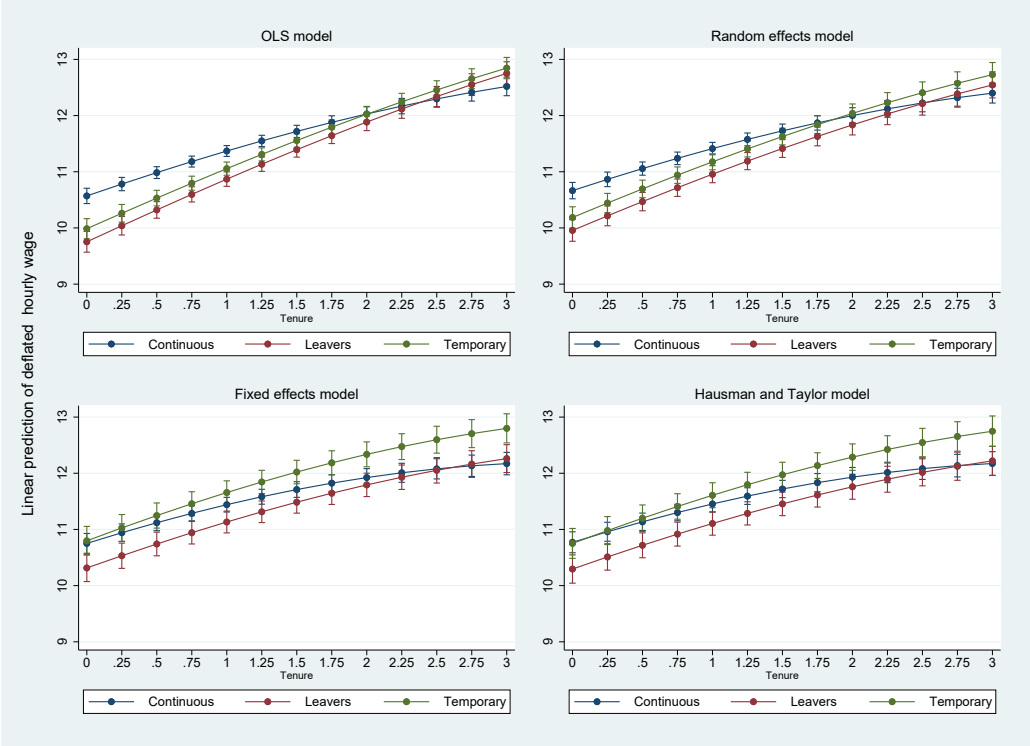
	OLS	Random Effects	Fixed Effects	Hausman-Taylor
Interruption Status (Ref: Continuer)				
Leaver (α_1)	-0.0804***	-0.0688***	-0.0415***	-0.0452***
	(0.0115)	(0.0118)	(0.0158)	(0.0158)
Temporary Interrupter (α_2)	-0.0568***	-0.0459***	0.0043	-0.0018
	(0.0109)	(0.0113)	(0.0162)	(0.0161)
Education level				
(Ref: Post-secondary without certificate)				
Private business or training school	0.0337**	0.0355**	0.0423*	0.0491**
	(0.0135)	(0.0162)	(0.0220)	(0.0220)
College or Cegep	0.0866***	0.0820***	0.0586***	0.0588***
	(0.0063)	(0.0070)	(0.0090)	(0.0090)
University	0.1934***	0.1792***	0.1279***	0.1285***
	(0.0084)	(0.0089)	(0.0102)	(0.0102)
Tenure (μ_1)	0.0811***	0.0766***	0.0725***	0.0718***
	(0.0061)	(0.0059)	(0.0069)	(0.0069)
Leaver X Tenure (ϕ_1)	0.0366***	0.0285***	0.0132	0.0133
	(0.0093)	(0.0089)	(0.0098)	(0.0098)
Temporary Interrupter X Tenure (ϕ_2)	0.0295***	0.0256***	0.014	0.0149
	(0.0093)	(0.0091)	(0.0099)	(0.0099)
Tenure2 (μ_2)	-0.0082***	-0.0088***	-0.0104***	-0.0103***
	(0.0010)	(0.0010)	(0.0011)	(0.0011)
Leaver X Tenure2 (θ_1)	-0.0012	-0.0006	0.001	0.001
	(0.0014)	(0.0013)	(0.0015)	(0.0015)
Temporary Interrupter X Tenure2 (θ_2)	-0.0007	-0.0005	0.0004	0.0004
	(0.0015)	(0.0014)	(0.0015)	(0.0015)
Male	0.0992***	0.1024***		0.1002***
	(0.0048)	(0.0061)		(0.0064)
Matrimonial Status (Ref : Single)				
Married or Living together	0.0605***	0.0534***	0.0412***	0.0414***
	(0.0065)	(0.0069)	(0.0081)	(0.0081)
Separated/Divorced/Widowed	0.0806*	0.0705	0.0528	0.0534
	(0.0481)	(0.0458)	(0.0512)	(0.0514)
Worked less than 30 hours=1	-0.1323***	-0.1134***	-0.0784***	-0.0784***
	(0.0058)	(0.0066)	(0.0081)	(0.0081)
Presence of both Parents	0.0239***	0.0285***		0.0397***
	(0.0061)	(0.0079)		(0.0086)
Number of siblings	0	0.0006		0.0011
	(0.0018)	(0.0025)		(0.0026)
Respondent's age in 1999 (Ref : 18 years)				
Age in 1999=19 years	0.0369***	0.0438***		0.0625***
	(0.0056)	(0.0072)		(0.0077)
Age in 1999=20 years	0.0641***	0.0749***		0.1031***
	(0.0063)	(0.0081)		(0.0088)
Constant	1.8566***	1.8299***	1.8517***	1.7760***
	(0.0159)	(0.0191)	(0.0369)	(0.0241)
Region specific effect	yes	yes	yes	yes
Period specific effect	yes	yes	yes	yes
Observations	24995	24995	24995	24995
Sargan-Hansen (Statistic)				20.1311
Sargan-Hansen (P-Value)				0.0646

Panel-robust standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

We present corresponding predicted wage growths in Figure 9. Previous results from cohort A still hold here. The average wage of interrupters evolves faster than those of their non-interrupter counterparts. Temporary interrupters have the fastest wage growth. And after a while, there is a wage gap in favor of Temporary Interrupters. This rapid growth of temporary interrupters enables to compensate whatever early identified wage penalty.

Figure 9: Estimation of the wage growth, YITS Cohort B (Restricted panel)



6 Conclusion

Dropping out of post-secondary education is seldom a permanent decision. Indeed, many individuals interrupt temporarily their schooling to return to a different institution or program. These individuals are referred to as Stopouts or Temporary Interrupters to be distinguished from Stayouts or Leavers who ultimately do not return. Continuers are those who never interrupted their schooling. With the emergence of panel data on educational and labor market pathways such as the National Longitudinal Survey of Youth (NLSY) in the USA and the Youth in Transition Survey (YITS) in Canada, there is growing evidence of these stopouts behaviors.

Previous studies focused on the factors explaining dynamics of school interruptions and re-enrollments but the effects of temporary interruptions on wages haven't been sufficiently investigated empirically. Using longitudinal data from the Youth in Transition Survey in Canada, we provide empirical evidence on the impact of both permanent and temporary school interruptions on wages in this study. We pose as Light (1995b) that school interruption and/or re-enrollment are correlated with time-invariant personal characteristics, and not with transitory wage shocks. This enabled us to resort to panel econometric strategies to analyze the impact of both permanent and temporary school interruptions on wages. We analyze two distinct cohorts of YITS : a younger but homogeneous cohort in terms of age and educational histories (Cohort A) and an older but less homogeneous cohort in terms of age and educational histories (Cohort B).

Our results are robust across these two cohorts and show that there is a very slight wage penalty less than 5% associated to both permanent and temporary post-secondary interruption. These results are in line with Griliches (1980); Marcus (1984) and contrast those of Griliches and Mason (1972); Featherman and Carter (1976) and Light (1995b) who rather found a significant wage penalty. Fortin and Ragued (2017) rather showed that different reasons for interruption seem to balance one another. Some methodological, data difference, distinction between stayouts and stopouts can be evoked to explain these differences. Our study also shows that the wage of Temporary Interrupters evolves very rapidly compared to Leavers and Continuers. Indeed, Temporary Interrupters benefit from better prospects on the labor market to tailor conveniently their skills. These results are relevant for educational policies.

Our study possesses certain features that must be underscored when analyzing our results. Firstly, the career start age of majority of our respondents particularly those from Cohort A is 17 years (18-20 years for Cohort B). These early ages help to account for large amounts of unmeasured early work experience and thus affecting our estimations (Light, 1998). This need to be put into perspective when comparing our results to other studies using different career starting dates. Indeed, Light (1998) showed that the wage effects of schooling are likely to be sensitive to the choice of a career starting date because it influences which wage observations are included in the sample, the schooling levels associated with each reported wage and finally the amount of work experience that is considered. Secondly, owing to the nature of the YITS, our sample is relatively young. At the final cycle, Cohort A's respondents were aged 25 years old. In cohort B, they were 26-28 years old. Given these relatively young ages, we can't ascertain that post-secondary graduates had sufficient time to establish themselves conveniently in the labor market. In the literature, researchers typically use samples of individuals where the upper range age limit is around 30-35 years Griliches and Mason (1972); Marcus (1984); Light (1995b); Fortin and Ragued (2017). Thus, it is also noteworthy to emphasize that the wages in this study relate likely to early career wages due to the relative young age of our sample.

This study can be enriched by accounting for duration and reasons of school interruption. Fortin and Ragued (2017) showed that the effect of discontinuous schooling on wages is dependent on the reason behind it. However the nature of our data rendered it difficult to account for these factors. An interesting area for future research will consist in modeling simultaneously schooling decisions and labor market in a structural way. A structural dynamic programming model of schooling decisions with unobserved heterogeneity in school and market ability where wages are estimated flexibly will help deepen our understanding. Belzil and Hansen (2002) and Belzil et al. (2017) develop such a framework which can be extended to incorporate discontinuities in schooling.

Appendix

Table 6: Summary statistics on average nominal and deflated hourly wage, YITS Cohort B

		Nominal hourly wage				Deflated hourly wage (IPC Base=2000-2001)			
Period	Interruption Status	Average	Median	Sd	Observations	Average	Median	Sd	Observations
Cycle 1 1999	Continuer	8.25	7.40	2.82	7776	8.58	7.69	2.93	7776
	Leaver	8.17	7.50	2.68	366	8.49	7.80	2.78	366
	Temporary Interrupter	8.24	7.50	2.65	421	8.56	7.80	2.75	421
Cycle 2 2000-2001	Continuer	10.18	9.00	4.24	5610	10.18	9.00	4.24	5610
	Leaver	9.71	8.59	3.88	1658	9.71	8.59	3.88	1658
	Temporary Interrupter	9.53	8.50	3.98	3059	9.53	8.50	3.98	3059
Cycle 3 2002-2003	Continuer	12.76	11.30	5.76	3992	12.59	11.14	5.68	3992
	Leaver	11.48	10.00	4.85	1998	11.32	9.86	4.78	1998
	Temporary Interrupter	12.14	10.63	5.65	2683	11.97	10.48	5.57	2683
Cycle 4 2004-2005	Continuer	16.00	14.55	8.28	2263	15.12	13.75	7.82	2263
	Leaver	14.23	12.74	6.27	2000	13.44	12.04	5.92	2000
	Temporary Interrupter	15.62	14.00	7.37	2460	14.76	13.23	6.96	2460
Cycle 5 2006-2007	Continuer	19.77	18.16	11.02	1114	17.92	16.46	9.99	1114
	Leaver	18.22	16.75	8.34	1805	16.52	15.19	7.56	1805
	Temporary Interrupter	20.55	19.00	9.62	2032	18.63	17.23	8.72	2032

Table 7: Tenure (in years), YITS Cohort B

Period	Interruption Status	Average	Median	Sd	Observations
Cycle 1	Continuer	0.82	0.42	0.77	7768
	Leaver	0.79	0.50	0.79	366
	Temporary Interrupter	0.85	0.58	0.77	420
Cycle 2	Continuer	1.10	0.58	1.08	5608
	Leaver	1.18	0.75	1.10	1657
	Temporary Interrupter	1.22	0.83	1.09	3059
Cycle 3	Continuer	1.42	0.92	1.41	3992
	Leaver	1.68	1.25	1.51	1997
	Temporary Interrupter	1.55	1.17	1.46	2682
Cycle 4	Continuer	1.76	1.25	1.70	2263
	Leaver	2.17	1.67	1.88	1998
	Temporary Interrupter	2.02	1.50	1.80	2457
Cycle 5	Continuer	2.19	1.50	2.01	1114
	Leaver	2.72	2.17	2.26	1804
	Temporary Interrupter	2.74	2.25	2.18	2030

Table 8: Estimation of the wage equation, YITS Cohort B (Non-Restricted panel)

	OLS	Random Effects	Fixed Effects	Hausman-Taylor
Interruption Status (Ref: Continuer)				
Leaver (α_1)	-0.0820***	-0.0727***	-0.0383***	-0.0405***
	(0.0093)	(0.0094)	(0.0134)	(0.0134)
Temporary Interrupter (α_2)	-0.0575***	-0.0514***	-0.0033	-0.0086
	(0.0088)	(0.0090)	(0.0140)	(0.0140)
Education level				
(Ref: Post-secondary without certificate)				
Private business or training school	0.0305***	0.0309**	0.0255	0.0319
	(0.0111)	(0.0129)	(0.0205)	(0.0204)
College or Cegep	0.0864***	0.0846***	0.0636***	0.0643***
	(0.0051)	(0.0056)	(0.0078)	(0.0078)
University	0.1848***	0.1764***	0.1273***	0.1283***
	(0.0073)	(0.0077)	(0.0089)	(0.0089)
Tenure (μ_1)	0.0708***	0.0671***	0.0620***	0.0613***
	(0.0049)	(0.0048)	(0.0060)	(0.0060)
Leaver X Tenure (ϕ_1)	0.0356***	0.0309***	0.0161*	0.0159*
	(0.0079)	(0.0076)	(0.0086)	(0.0086)
Temporary Interrupter X Tenure (ϕ_2)	0.0309***	0.0293***	0.0205**	0.0210**
	(0.0078)	(0.0077)	(0.0088)	(0.0088)
Tenure2 (μ_2)	-0.0069***	-0.0072***	-0.0088***	-0.0087***
	(0.0009)	(0.0009)	(0.0010)	(0.0010)
Leaver X Tenure2 (θ_1)	-0.0013	-0.0011	0.0002	0.0002
	(0.0012)	(0.0012)	(0.0013)	(0.0013)
Temporary Interrupter X Tenure2 (θ_2)	-0.0012	-0.0013	-0.0008	-0.0008
	(0.0013)	(0.0013)	(0.0014)	(0.0014)
Male	0.1001***	0.1022***		0.1011***
	(0.0038)	(0.0047)		(0.0049)
Matrimonial Status (Ref : Single)				
Married or Living together	0.0562***	0.0509***	0.0414***	0.0420***
	(0.0056)	(0.0060)	(0.0074)	(0.0074)
Separated/Divorced/Widowed	0.0485	0.0452	0.0592	0.0597
	(0.0409)	(0.0393)	(0.0434)	(0.0436)
Worked less than 30 hours=1	-0.1320***	-0.1195***	-0.0847***	-0.0851***
	(0.0045)	(0.0050)	(0.0067)	(0.0067)
Presence of both Parents	0.0263***	0.0286***		0.0372***
	(0.0049)	(0.0059)		(0.0064)
Number of siblings	0	0.0002		0.0002
	(0.0015)	(0.0018)		(0.0019)
Respondent's age in 1999 (Ref : 18 years)				
Age in 1999=19 years	0.0333***	0.0374***		0.0559***
	(0.0045)	(0.0056)		(0.0061)
Age in 1999=20 years	0.0662***	0.0733***		0.1013***
	(0.0050)	(0.0061)		(0.0069)
Constant	1.8519***	1.8361***	1.8663***	1.7956***
	(0.0120)	(0.0136)	(0.0300)	(0.0176)
Region specific effect	yes	yes	yes	yes
Period specific effect	yes	yes	yes	yes
Observations	36444	36444	36444	36444
Sargan-Hansen (Statistic)				30.7225
Sargan-Hansen (P-Value)				0.0022

Panel-robust standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure 10: Estimation of the wage growth, YITS Cohort B (Non-Restricted panel)

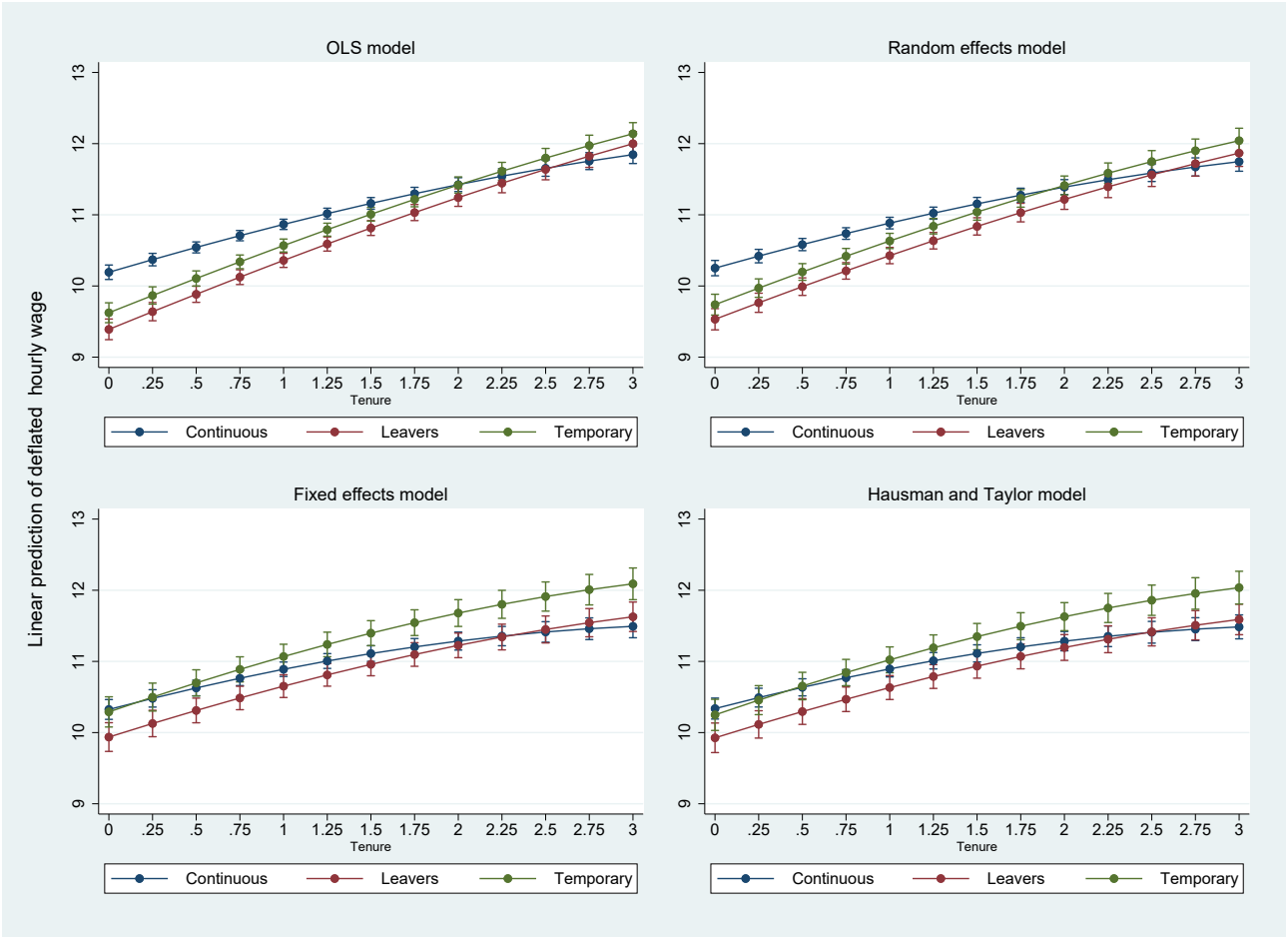


Table 9: Estimation Sample Means and Standard Deviations

	Cohort A				Cohort B			
	Non-Restricted Panel		Restricted Panel		Non-Restricted Panel		Restricted Panel	
Variables	Average	sd	Average	sd	Average	sd	Average	sd
Interruption Status								
Continuer	0.73	0.45	0.71	0.45	0.54	0.50	0.51	0.50
Leavers	0.20	0.40	0.21	0.40	0.20	0.40	0.22	0.41
Temporary Interrupter	0.08	0.27	0.08	0.28	0.26	0.44	0.27	0.44
Education level								
Post-secondary without certificate	0.62	0.49	0.56	0.50	0.54	0.50	0.48	0.50
Private business/taining school	0.02	0.15	0.02	0.15	0.03	0.18	0.03	0.18
College/cegep	0.19	0.39	0.20	0.40	0.25	0.43	0.26	0.44
University	0.17	0.38	0.22	0.41	0.18	0.38	0.22	0.42
Tenure (in years)	1.26	1.27	1.35	1.35	1.47	1.53	1.60	1.64
Male	0.44	0.50	0.45	0.50	0.45	0.50	0.45	0.50
Matrimonial Status								
Single/never married	0.85	0.36	0.82	0.38	0.81	0.39	0.77	0.42
Married/Living together	0.15	0.35	0.17	0.38	0.19	0.39	0.23	0.42
Separated/Divorced/Widowed	0.00	0.05	0.00	0.05	0.00	0.06	0.00	0.07
Region								
Newfoundland	0.06	0.24	0.06	0.23	0.04	0.20	0.04	0.19
Prince Edward Island	0.05	0.22	0.05	0.22	0.02	0.15	0.02	0.15
Nova Scotia	0.10	0.30	0.10	0.30	0.06	0.24	0.06	0.24
New Brunswick	0.09	0.28	0.08	0.27	0.05	0.22	0.05	0.21
Quebec	0.18	0.39	0.19	0.39	0.21	0.41	0.23	0.42
Ontario	0.17	0.37	0.16	0.37	0.31	0.46	0.30	0.46
Manitoba	0.08	0.27	0.08	0.27	0.07	0.25	0.07	0.26
Saskatchewan	0.07	0.26	0.08	0.27	0.06	0.24	0.06	0.25
Alberta	0.11	0.32	0.12	0.32	0.09	0.29	0.10	0.30
British Columbia	0.09	0.28	0.08	0.28	0.07	0.26	0.07	0.26
Autres Territoires	0.00	0.05	0.00	0.05	0.00	0.04	0.00	0.04
Worked less than 30 hours	0.25	0.43	0.24	0.43	0.25	0.44	0.23	0.42
Nominal hourly wage (End Job)	12.14	6.73	12.89	7.15	12.05	6.68	12.89	7.23
Deflated hourly wage (End Job)	11.26	5.93	11.85	6.27	11.73	6.12	12.43	6.59
Living with both parents	0.88	0.32	0.88	0.32	0.84	0.37	0.84	0.36
Number of siblings	1.77	1.14	1.77	1.13	1.78	1.30	1.77	1.27
Age in 1999 (Cohort B)								
Age=18 years					0.34	0.48	0.36	0.48
Age=19 years					0.36	0.48	0.36	0.48
Age=20 years					0.30	0.46	0.28	0.45
Observations	35767		25062		36444		24995	

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