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The Effect of High School Employment on Educational Attainment : A Conditional Difference-in-Differences Approach

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Abstract

Using American panel data from the National Educational Longitudinal Study of 1988 this paper investigates the effect of working during full-time education on attainment. In particular the focus is on students in the twelfth grade of high school. By employing a propensity score matching approach combined with difference-in-difference methods we attempt to overcome problems of sample selection and unobserved heterogeneity in order to estimate an unbiased effect of working during high school. Results indicate that once such factors are controlled for, little to no effect on reading and math scores are found. Neither do we find evidence of a negative impact for those who work long hours per week. We thus argue that working during schooling (twelfth grade) has little detrimental impact on grades *per se*.

Abstract

En s'appuyant sur des données de panel américaines (*National Educational Longitudinal Study of 1988*), cet article étudie l'effet sur la réussite scolaire d'occuper un emploi pendant ses études. Nous étudions en particulier le cas des étudiants en fin de *high school* (grade 12). Afin d'estimer l'effet causal du travail à temps partiel sur la réussite, nous contrôlons de la sélection sur observables et inobservables à l'aide d'une approche de type différence de différences conditionnelle. Les résultats indiquent un effet causal négligeable du travail à temps partiel sur des tests en lecture et mathématiques passés en fin de *high school*, ceci même pour ceux qui occupent un emploi intensif.

JEL Classification: J24, J22, I21

1 Introduction

There has, in recent years, been an upsurge in the number of studies examining the effects of working part-time while studying. The "employment effect" is typically considered with respect to educational outcomes, but also with respect to post-school wages and employment probabilities. Some authors, such as Warren, LePore and Mare (2000), argue that "studies of life" have typically treated educational careers and occupational careers as mutually exclusive and that only recently attention has been garnered toward examining the relationship between students who work and their educational achievements. Such research suggests that there is a high level of interaction between "earning" and "learning". Nonetheless, whilst it is true that the subject of working during school hours is gaining popularity in the literature, the phenomenon of working during education has been known for some time to both sociologists and economists.

It has now been over two decades since both D'Amico (1984) and Michael and Tuma (1984) observed that employment among young people in the education system is remarkably high. Michael and Tuma remark that: "Among 14- and 15- year-old students in 1979, about one in four was employed [and that] this is not a trivial rate of employment" (p. 466). Likewise D'Amico noted that employment intensity increases rapidly as age progresses, from approximately 40 percent for those in grade 10 to 70 percent for those in grade 12. It was here that some of the first questions about the effect of working during school on attainment and post-educational outcomes were raised.

Such questions are primarily concerned with whether working during schooling can be seen as a substitute or as a complement to education. Part-time work during schooling can be seen as a substitute to education because any additional increase in time spent working can, *ceteris paribus*, lead to a reduction in time spent on education. This, in turn, might negatively affect any educational outcomes. Alternatively, it may be that working complements educational attainment *via* the acquisition of a variety of skills such as improved work values, ethics, literacy and numeracy skills. If one assumes that such skills are general and transferable, it is possible that individuals who work whilst in full-time education might have a learning advantage compared to those who do not (Holland and Andre, 1987).

Whilst the debate on the effect of working during schooling has taken nearly two decades to reach some consensus, most of the existing studies show that working particularly long hours during school has a detrimental impact on educational attainment. However, there is also evidence from the literature that working a small amount of hours may be beneficial to studying. Working during school can thus both be a complement or a substitute to education, depending on the amount of hours worked. Nonetheless, important questions remain, namely in the theoretical and methodological nature of this topic.

From a theoretical view various theories have been put forwards in an attempt to explain such empirical findings. These range from time-allocation models to socialisation arguments. However, little agreement has been reached to what extent these models are applicable and what the casual nature of such these theories might be (Warren, 2002). Furthermore, using more realistic "life" assumptions, recent methodological advancements have cast doubt on the robustness of earlier obtained results. This has led to the implementation of instrumental variable estimators into some of recent research (Ehrenberg and Sherman, 1987; Lillydahl, 1990; Singh, 1998; Warren, LePore and Mare, 2000; Tyler, 2003; Stinebrickner and Stinebrickner, 2003; Rothstein, 2007). However, instrumental variable techniques rely on the selection of suitable instruments and it is often difficult to prove conclusively that the selected instrumental variables respect the corresponding identifying assumption. In this paper we hope to address such issue using empirical techniques from the evaluation literature, which do not implicitly rely on the choice of instruments, in order to estimate the causal effect of part-time work during grade 12 on educational attainment.

The remainder of this paper is set out as follows. In section 2 we explore some of the trends in working during schooling by young people in the United States. Section 3 will highlight some of the competing theories regarding the effect of part-time work on educational attainment and prove an overview of previous findings in the literature. Section 4 outlines a theoretical model of the decision to work part-time. Section 5 provides a brief overview of the National Education Longitudinal Study of 1988 (NELS88) and its associated descriptive statistics. Section 6 describes the empirical analysis whilst section 7 presents the results. Finally section 8 concludes.

2 Youth employment during schooling in the United States

It should be remembered that whilst the minimum school-leaving age in the United States is at age 16, the minimum legal working age is age 14 or above.[1] Even those below the minimum legal working age may find part-time employment in jobs such as babysitting or delivering newspapers. This implies that a substantial part of the schooling population is eligible to perform some function in the labor market, and therefore, one cannot separate the education and the labor market completely.

[1]Note that state-wise variations exist.

The Youth Labor Force 2000 report, by the Bureau of Labor Statistics, finds that during the 1996-1998 period 2.9 million 15 to 17 year olds worked during school months, while during the summer months this increased to 4 million. It appears that the number of people working increases with age and "at age 12, half of the American youths engage in some type of work activity" (p. 20). This number increases to over half (57%) for 14 year olds and to 64% for those aged 15. By age 16 to 17 over 80 percent of individuals will have held a part-time job. Furthermore, as age progresses the nature of work appears to formalise from freelance work into a more mature and binding employment relationship. Evidence from the literature finds likewise proportions, and of those who do work, the work intensity is substantial and increasing (Ruhm, 1995 and Singh, 1998).

Such findings are echoed by the 1991 Oregon Task Force report on child labor activity, which finds that the numbers of 16-17 year olds working part-time in education is increasing and argues that many of these jobs are low-paying, unfulfilling and instil little academic skills.

However, it should also be noted whilst educators and policy makers generally find working during education undesirable and counter-productive, many schools, districts and states continue to implement formal school-to-work programmes (Warren, 2002). This seemingly paradoxical consequence may lie in the opposing views held by members of society on the impact that working has during schooling and on the widely disparaging results obtained by literature.

3 Literature review

Several theoretical approaches exist which attempt to explain the relationship between working during full-time education and attainment. The most frequently cited is the time allocation based theory (or zero-sum model). A further approach is the socialisation based argument (or developmental model). Finally, an alternative theory, the primary orientation approach, is put forward by Warren (2002).

3.1 Time allocation explanations - Zero-sum model

The time theoretical perspectives of working part-time during education are based on the zero-sum model (Coleman, 1961; D'Amico, 1984; Marsh; 1991; Warren, 2002). The zero-sum model argues that time has a finite horizon and any additional time spent on employment during education must lead to a reduction in time spent on educational advancement, *ceteris paribus*. Furthermore, besides a reduction in the actual number of hours spent on school work, sustaining high levels of commitment at the workplace may have an adverse and opposite effect on school level aspirations (Marsh, 1991; Worley, 1995). Additionally, participation in extra-curricular activities such as sport and youth clubs, which improve psychological adjustment and commitment to schooling, may be hampered by those in part-time employment (Lewin-Epstein, 1981; D'Amico, 1984).

However, there may be positive aspects to the zero-sum model. Viewed from a human capital perspective, if one assumes that educational skill accumulation suffers from diminishing marginal returns and that working part-time during schooling results in a positive amount of skill accumulation, then the net "pay-off" to attainment from working few hours per week may be larger than working a few hours more on homework per week. In other words, the marginal return of working during full-time education might be higher than the marginal return of schooling under specific conditions. There is also a "keep them off the streets" argument (Greenberg and Steinberg, 1986). The zero-sum model is thus not necessarily incompatible with positive returns to education from working part-time.

3.2 Socialisation arguments - Developmental model

The "socialisation" argument, as outlined by Schoenhals, Tienda and Schneider (1998), argues that socialisation effects result when students learn new abilities or attitudes which persist post school employment. Positive aspects of the socialisation model are that employment during full-time education "builds character" in young individuals (Greenberg and Steinberg, 1986) and improves personal, family and social interaction (Phillips and Sandstrom, 1990). Evidence by Schill, McCartin and Meyer (1995) suggests that working exhibits positive effects on cognitive and developmental skills. Certain skills such as (collective) responsibility, professional interaction and cooperation are unlikely to be taught at school in such overt forms. Finally there is the "reverse psychology" argument, which states that individuals who work during schooling, may become so dreaded and disillusioned with working that it motivates them into staying in the education system (Mortimer *et al*, 1992).

Critics of the socialisation argument point out that youth employment rarely offers much responsibility, little cooperation and little to no training which could be classed as human capital accumulation. Further negative socialisation effects may come from increases in delinquency and deviance amongst youths. This might lead to less positive attitudes towards school and hence lower educational attainment.

3.3 Primary Orientation approach

Warren (2002), alternatively, argues that "... the association between employment intensity and school performance may have more to do with social psychological factors than with resources allocation, and that a primary orientation model best explains why students who work also tend to do badly at school". Students who are unobservably positively inclined towards schooling will achieve higher attainment scores regardless of their employment intensity. Those that are unobservably negatively inclined towards schooling will do less well. Students' social and psychological orientation towards work is what determines their educational outcomes and employment intensity is merely an indicator of the extent to which they are work orientated.

To conclude, the theoretical predictions are ambiguous. Part-time work during schooling may be seen as a substitute to educational attainment because any additional increase in employment time would lead to a reduction in time spent on education. However, it is also possible that it may complement educational attainment *via* the acquisition of a variety of skills. The importance of the nature of the relationship between part-time work and educational attainment is significant as different theoretical models have different policy implications. Evidence of a negative impact of working part-time should be corrected by limiting the maximum possible work hours according to the zero-sum model. The socialisation model would place emphasize on the "type" of work, as certain occupations may promote key skills required for learning more effectively. Finally, if poor school performance is the result of unobservable characteristics, as suggested by the primary orientation theory, a better solution would be to keep students engaged and motivated in the classroom. In other words, controlling and improving "unobservables" is the key to increasing attainment, rather than placing stricter regulation of working during school hours. Finally, it should be noted that none of these theories are mutually exclusive and that it may be difficult to distinguish between such differing effects.

3.4 Prior evidence

In the United States, much interest and debate has focused on the effects of working during full-time education. Some of these studies indicated reduced academic performance by students who worked (Greenberger and Steinberg, 1980; Marsh, 1991; Eckstein and Wolpin, 1999; Tyler, 2003; Stinebrickner and Stinebrickner, 2003), whilst others found no negative effect (Meyer and Wise, 1982; D'Amico, 1984; Green and Jacques, 1987; Mortimer, Finch, Shanahan, and Ryu, 1992; Schoenhals *et al.*, 1998;

Warren *et al*, 2000; Rothstein, 2007). Many studies, however, showed that the effects varied, depending on hours worked - that modest involvement in employment did not interfere with academic performance and was sometimes associated with a positive impact on grades, but intense involvement had negative effects - (Steinberg *et al*., 1982a; Schill *et al*., 1985; Lillydahl, 1990; Steel, 1991; Turner, 1994; Cheng, 1995; Singh, 1998; Oettinger, 1999). This appears to be the most predominant finding in the literature with an approximate inflection point varying between 10-20 hours of work per week.

Early empirical research into the effects of working whilst in education was conducted by Steinberg *et al* (1982), Steinberg and Greenberger (1980) and Greenberger *et al* (1980). However, more rigorous statistical analysis is introduced by D'Amico (1984) who uses OLS estimation to find that working part-time does not appear to have a detrimental effect on educational attainment. Marsh (1991), however, using High School and Beyond daya (HSB) finds a linear and negative relationship between work and test scores whilst Mortimer *et al* (1992) conclude that twelfth graders working less than 20 hours had significantly higher grades compared to those who worked 20 hours or more. Similar findings are produced by Steinberg *et al* (1982a) and Worley (1995) who argue that the number of hours worked per week has a significant negative impact on educational attainment.

It should be noted that some findings suggest that working few hours may be beneficial to educational attainment (D'Amico, 1984; Schill *et al*, 1985; Turner, 1994; Steel, 1995). These studies find that pupils working few hours per week are likely to have higher educational achievement compared to those who work long hours or no hours at all. However, a potential problem with the above findings is their failure to take into account the possible endogeneity and sample selection of working part-time during schooling.

In one of the first papers to address such issues, Ehrenberg and Sherman (1987) acknowledge the issue of endogeneity and argue that "[the previous literature] is not completely satisfactory in that it fails to control for the possibilities that such employment is determined simultaneously with choice of college..." (p. 2). Using a two-stage approach they find that there does not appear to be an adverse effect on grade point average from working part-time during school, though there is a significant adverse effect on the probability of staying-on in education. Lilydahl's (1990) study, using the 1987 National Assessment of Economic Education Survey was another early adopter of two-stage least squares approach, also arguing that part-time work and educational attainment were likely to be simultaneously determined. Evidence by Ruhm (1997) suggests that OLS estimates are more likely to understate any effects of working part-time during schooling. Relying on selection methods, he notes that the Mills coefficient in his equations is positive and significant indicating that selection bias is taking place. Recent work by Eckstein and Wolpin (1999), Stinebrickner and Stinebrickner (2003), Dustman and van Soest (2007) and Rothstein (2007) continue to highlight the importance to take endogeneity and sample selection into account.

A number of previous studies have utilised the NELS 88 dataset to analyse the impact working part-time has on educational attainment. Singh (1998), using a structural equation approach, finds that working in grade 10 has a small detrimental effect on achievement in English, Reading and Social Science when gender, socioeconomic status and previous attainment are controlled for. Schoenhals, Tienda and Schneider (1999) also examine tenth grade achievement using OLS regression, and argue that the much cited adverse effect of working part-time during school on educational attainment is actually "...attributable to pre-existing differences among youth who elect to work at various intensities". Once such observable differences are taken into account any significant impact on educational attainment from working disappears. Warren, Lepore and Mare (2000) also find little evidence that there is a relationship between long or short term grades from working whilst in high-school.

Finally, Tyler (2003), arguably using a more robust econometric framework than previous NELS 88 studies, finds opposite results compared to the three previous studies. Using interstate variations in child labor laws as an instrument for students labor supply, he finds significant effects of part-time work on twelfth grade achievement and argues that OLS estimates severely underestimate the negative impact of working part-time during schooling. For example, where he finds coefficients of OLS which indicates that decreasing student work by 10 hours per week would increase twelfth grade maths score by 0.03 of a standard deviation, for IV estimates this increases to 0.20 of standard deviation. Tyler concludes that if government policy is to raise education standards, more restrictive child labor laws for individuals aged 16-17 ought to be considered.

Whilst we have only surveyed part of the literature it should be clear that the debate about the impact of working part-time during schooling on educational attainment is complex and multi-layered. Methodological advances such as sample selection procedures, IV estimation and simultaneous equation modeling have meant that the validity of some of the earlier results has been put to question. The main contribution of our paper lies in the fact that we rely on statistical techniques from the evaluation literature to control for observed and unobserved heterogeneity, without needing to instrument part-time work decisions.

4 The model

In this section, we present a model in which educational attainment, part-time work and the amount of time devoted to homework during high school are endogenous. This theoretical framework enables to rationalize our reduced-form empirical strategy that will be exposed later.

In the model, we assume that the student values his consumption C (throughout the academic year), his twelfth grade attainment S and time allocated to leisure T_l. Denoting by V the value function of the student and by $\widetilde{V}$ the component which is constant with respect to the choice variables, we have:

$$V = V(T_l, S, C) + \widetilde{V} \tag{1}$$

Note that the model supposes that students gain utility from the educational attainment itself. This specification is consistent with the Beckerian view, as it may result from expected lifetime earnings: a higher achievement during twelfth grade leads to an expectation of getting a higher degree, resulting therefore in higher expected earnings throughout lifetime. That may also stem from a social gratification directly resulting from academic achievement (consumption value of schooling).

When entering twelfth grade, the student is assumed to choose simultaneously the amount of time allocated respectively to part-time work (T_{pt}) and homework (T_h). Assuming that the total amount of time available outside of school (T) is the same for all students, the time constraint can be written as follows:

$$T = T_h + T_{pt} + T_l \tag{2}$$

The student rationally chooses the amount of time that he desires to devote to part-time work (T_{pt}^*) and homework (T_h^*), maximizing his value function :

$$(T_{pt}^*, T_h^*) = \arg\max_{(T_{pt}, T_h)} V \tag{3}$$

More precisely, as time allocated respectively to part-time work and homework are left-censored, T_{pt}^* and T_h^* defined above can be seen as latent variables underlying Tobit models[2]. Assuming the labor

[2]The latent variables T_{pt}^* and T_h^* can be respectively interpreted as the propensity to work part-time and to spend time doing homework.

market is in equilibrium, the actual amount of time allocated by the student to part-time work (T_{pt}) and homework (T_h) satisfy :

$$T_{pt} = \begin{cases} T^*_{pt} & \text{if } T^*_{pt} > 0 \\ 0 & \text{otherwise} \end{cases}$$

$$T_h = \begin{cases} T^*_h & \text{if } T^*_h > 0 \\ 0 & \text{otherwise} \end{cases}$$

Attainment S during twelfth grade is assumed to result from an attainment production function Π which positively depends on ability a, educational aspiration asp, time devoted to homework T_h, labor supply T_{pt} and unobserved individual heterogeneity ϵ in terms of academic achievement :

$$S = \Pi(a, asp, T_h, T_{pt}, \epsilon) \quad (4)$$

Therefore, we allow part-time work to have both an indirect effect (*via* the time constraint which implies that any additional time spent working while studying must lead to a reduction in the total amount of time devoted to homework and leisure) and a direct effect on attainment. The latter effect may result from skill accumulation : along with Holland and Andre(1987), part-time working can lead to an acquisition in academically related skills and knowledge, as well as “desirable" traits such as responsibility and maturity. Consequently, within this framework, the impact of part-time work on academic achievement is ambiguous. The net effect will depend on the returns, in terms of attainment, to homework compared with the returns to part-time work.

Along with its effect on time allocation and attainment, part-time work also leads to a higher level of consumption during the school year. The budget constraint faced by the twelfth grade student can be written as :

$$pC = y + \omega T_{pt} \quad (5)$$

Where p denotes the price of consumer good, y the parental financial transfer (net of tuition fees) received by the student and ω the hourly wage earned when participating to the labor market. We assume that ω is constant among twelfth grade students.

Hence, consumption is positively affected by part-time work :

$$C = \frac{y + \omega T_{pt}}{p} \tag{6}$$

It stems from the individual program that the amount of time devoted to part-time work (T_{pt}) and homework (T_h) are functions of the following arguments :

$$T_{pt} = T_{pt}(a, asp, y, \epsilon) \tag{7}$$

$$T_h = T_h(a, asp, y, \epsilon) \tag{8}$$

Finally, the model can be used to derive a binary part-time work decision :

$$\text{Part-time work during twelfth grade} \quad \Leftrightarrow \quad T^*_{pt}(a, asp, y, \epsilon) > 0 \tag{9}$$

This binary choice is the object of the Probit model which is estimated later in the empirical section.[3] Note that this framework can also be used to take into account non linearities in the effect of part-time work on educational attainment, as we can write :

$$\text{Part-time work (more than k hours)} \quad \Leftrightarrow \quad T^*_{pt}(a, asp, y, \epsilon) > k \tag{10}$$

Therefore, the model discussed above allows part-time work decisions to differ among students depending on schooling ability, educational aspiration, parental financial transfer and unobserved individual heterogeneity. Hence, observable factors such as standardized test scores taken as a proxy for ability, educational aspirations, parental income and number of siblings taken as a proxy for parental financial transfers will be included in the following empirical estimations of part-time work decisions.

5 Data and descriptive statistics

The data used in this study are from the National Education Longitudinal Study 1988 (NELS88) conducted by the National Center for Education Statistics. It is a nationally representative sample of students who were eight graders in the base year of 1988. Further follow up surveys were conducted in

[3] Note that the latent variable underlying the Probit model can be interpreted as the propensity to work part-time.

1990 (tenth grade), 1992 (twelfth grade), 1994 and 2000, giving a total of 5 waves. Making use of the "public use file 88/92" we have a total set of 27,394 cases. However, after restricting our analysis to those who are eligible and still in school by grade 12 we are left with 16,663 observations. Missing values for gender reduce this to 15,747 and finally, dropping missing values for part-time work (in any grade) and test scores (in any grade) leaves us with 9,887 individuals.

The NELS88 dataset contains a large amount of information about the students, their social background, their relatives and friends, the characteristics of their school, their success at school and their way of life. The longitudinal nature of the dataset gives a good opportunity to track the behavior of pupils and their success later on. Of special interest in our study is the fact that the first three waves of the survey include standardized tests in four disciplines: Maths, Sciences, History and Reading. These tests were taken at the time of the interview and make it possible to follow the progression of students across time. Their standardization makes them comparable both in the time and in the cross section dimensions. The dependent variables for educational attainment in this study are the composite score of Maths and Reading tests. This choice is motivated by the synthetic nature of this index which is likely to take into account the different ability required from the pupils to succeed in high school.

Furthermore, the NELS88 survey has detailed questions about the part-time work behavior of students with information about the intensity of work performed and the type of occupation. We are able to track the amount of hours and occupation type worked in grades 8, 10 and 12 (see Table 1 for the change in hours according to schooling level). We find that the composition of occupation and hours changes significantly over the different grades. For example, we find that in grade 8 approximately 70% of teenagers had a part-time job during school (mostly working between 0-10 hours per week). However, by grade 10 only 62% of males worked during school whilst only 51% of females worked. By grade 12 the proportions changed to 65% of males working and to 68% of females working. What explains this sudden dip of individuals working in grade 10? And why is the incidence of work highest in grade 8 when most of the literature states that the propensity to work increases with age?

The answer seems to lie in occupational type. Upon further investigation it appears that the majority of work held by males in grade 8 is lawn work and newspaper routes (47% for males working in grade 8). Females are predominantly occupied as babysitters (76% of all working females). Furthermore, the hours worked associated with such types of occupation are typically low (mostly less than 4 hours per week). By grades 10 and 12 the incidence of lawn work and babysitting drops dramatically (only 8%

	Males		Females	
	Frequency	*Percent*	*Frequency*	*Percent*
Grade 8				
Not Working	1,401	29.63	2,594	32.96
Working 0 to 10 hours	2,617	55.35	4,558	57.92
Working 11 to 20 hours	389	8.23	457	5.81
Working 21 or more hours	321	6.79	159	3.08
Grade 10				
Not Working	1,817	38.43	2,563	49.68
Working 0 to 10 hours	904	19.12	1,015	19.67
Working 11 or more hours	899	19.01	858	16.63
Working 21 or more hours	1,108	23.43	723	14.01
Grade 12				
Not Working	1,649	34.88	1,649	31.96
Working 0 to 10 hours	764	16.16	981	19.02
Working 11 or more hours	1,222	25.44	1,645	31.89
Working 21 or more hours	1,093	24.39	884	17.14
Total	4,728	100	5,159	100

Table 1: Sample proportions of the incidence of work according to grade

of working females still babysit and only 5% of working males are occupied with lawn work) and shifts towards activities such as grocery clerks, fast food workers and salespersonel. At the same time, the amount of hours worked with such activities increases and most of the people holding a part-time job work 11 to 20 hours per week during high school.

Moreover, examining transition matrices we find that 57% of people who did not work in grade 10 work during high school in grade 12. 48% of individuals increase their hours from less than 10 hours in grade 10 to 11 hours or more. 40% of individuals who worked in grade 10 decide not to work in grade 12. No discernable pattern can be found in occupational changes from grade 10 to 12. The absence of a clear pattern of continuity in the transitions continues to underscore the flexible and fluid nature that the part-time work process is, and as such, one could argue that the lack of association between part-time work (measured by intenstity or occupation) over different grades suggests that current part-time work experiences are unlikely to be dependent on past work experiences.

The descriptive evidence therefore suggests that the decision to work during school is rather complex. Working behavior displays substantial differences when examined in different grades and occupations and whilst previous research has identified the importance of the intensity of working within the working decision, our descriptives suggest that occupational choices also matter.

Table

	Males						*Females*					
	Gr12 Math Score Yes			*Gr12 Math Score No*			*Gr12 Math Score Yes*			*Gr12 Math Score No*		
Individuals who have ...	*Freq.*	*Mean*	*SD*	*Freq.*	*Mean*	*SD*	*Freq.*	*Mean*	*SD*	*Freq.*	*Mean*	*SD*
PTJ12†	3079	53.51	9.38	1649	54.14	10.41	3510	52.18	9.03	1649	52.47	10.04
PTJ12 and works 0 to 10 hours per week	764	55.95	9.41	3964	53.30	9.77	981	54.45	9.07	4178	51.76	9.36
PTJ12 and works 11 to 20 hours per week	1222	54.36	8.98	3506	53.51	10.01	1645	52.17	8.88	3514	52.32	9.58
PTJ12 and works 21 or more hours per week	1093	50.85	9.18	3635	54.59	9.76	884	49.67	8.58	4275	52.81	9.43
PTJ12 but does not work as a babysitter, lawn or household worker	2905	53.47	9.37	1823	54.13	10.34	884	49.67	8.58	1984	52.49	9.87
PTJ12 but only salespersons, fast food workers or grocery clerks	1317	53.98	9.10	3411	53.63	10.00	1873	52.10	8.81	3286	52.37	9.66
PTJ12 and increased their work hours from grade 10	1367	54.56	9.75	3361	53.39	9.74	1066	53.13	9.67	4093	52.05	9.27
Work weekends only in grade 12	642	55.39	9.51	4086	53.47	9.77	679	54.34	8.81	4480	51.96	9.40
	Gr12 Reading Score Yes			*Gr12 Reading Score No*			*Gr12 Reading Score Yes*			*Gr12 Reading Score No*		
Individuals who have ...	*Freq.*	*Mean*	*SD*	*Freq.*	*Mean*	*SD*	*Freq.*	*Mean*	*SD*	*Freq.*	*Mean*	*SD*
PTJ12	3079	51.69	9.44	1649	51.58	10.61	3510	53.36	8.74	1649	53.27	9.61
PTJ12 and works 0 to 10 hours per week	764	53.63	9.52	3964	51.27	9.88	981	55.36	8.72	4178	52.86	9.03
PTJ12 and works 11 to 20 hours per week	1222	52.42	9.11	3506	51.39	10.10	1645	53.47	8.49	3514	53.27	9.27
PTJ12 and works 21 or more hours per week	1093	49.53	9.34	3635	52.29	9.93	884	50.95	8.65	4275	53.83	9.03
PTJ12 but does not work as a babysitter, lawn or household worker	2905	51.67	9.41	1823	51.63	10.55	3175	53.31	8.75	1984	53.38	9.45
PTJ12 but only salespersons, fast food workers or grocery clerks	1317	52.29	9.02	3411	51.41	10.16	1873	53.30	8.46	3286	53.35	9.34
PTJ12 and increased their work hours from grade 10	1367	52.16	10.01	3361	51.45	9.80	1066	54.24	9.24	4093	53.10	8.96
Work weekends only in grade 12	642	52.78	9.92	4086	51.48	9.85	679	55.31	8.36	4480	53.03	9.09

† Part time job in grade 12

Table 2: Twelfth Grade Standardized Test Score according to Part-time Jobs

6 Empirical analysis

6.1 Methods applied in recent studies

Whilst early research into the effect of working on educational attainment paid little attention to the endogeneity of working, recent work revolves strongly around correctly accounting for unobserved individual heterogeneity within the hours worked decision. Unobservables are likely to drive the work decision, even when a multitude of explanatory factors are included in the econometric framework. Eckstein and Wolpin (1999) adopt a structural approach and use the Heckman-Singer method to control for unobserved individual heterogeneity and develop a dynamic model of high school attendance and work decision. Other researchers such as Singh (1998) and Warren *et al* (2000) use structural equation modeling to simultaneously estimate both the work decision and educational outcomes. Finally, Tyler (2003), Stinebrickner and Stinebrickner (2003) and Rothstein (2007) use a combination of 2-stage and/or fixed effect procedures. Identification issue remains crucial for all these studies.

Since traditional regression methods typically use parametric specifications to account for differences in observable characteristics between working students and non-working students, they implicitly estimate the potential outcome in the non-working state as the fitted value on the regression functional. Since the nonparametric analysis became more popular, such methods have been criticised in the literature: parametric regression models might not be flexible enough to capture the true relationships and often rely on arbitrary identification assumptions, which allow the researcher to extrapolate into areas of the regressors for which no observations are available and hide the lack-of-overlap (see Heckman, Lalonde and Smith (1999) for more details). Our estimation of the work effect relies on non-parametric and semi-parametric approaches that require less functional form assumptions when controlling for both observable and unobservable characteristics.

6.2 Identification issue

The identification strategy of the causal effect of working part-time during twelfth grade follows the framework developed by Roy (1951) and Rubin (1974). Calling YT the outcome of a working student, and YC the outcome of a non-working student, this framework assumes that a causal effect of working part-time relative to not working can be identified as an effect of treatment-on-the-treated when comparing the results of working individuals (YT) for which we know their working status ($D = 1$) with the hypothetical situation of the same individuals if they had not worked ($YC|D = 1$).

An outcome of non-working is counterfactual for part-time working students and cannot be observed directly from the data. Given that the average parameter of interest is the effect of part-time work for the population choosing to work in 12h grade, the effect of treatment-on-the-treated is given by the difference between observed and counterfactual outcomes

$$\mathrm{E}(YT|D = 1) - \mathrm{E}(YC|D = 1) \tag{11}$$

The main problem actually consists of identifying $\mathrm{E}(YC|D = 1)$. In principle, two alternative approaches can be applied to identify the average non-work outcome: relying on the situation of working students before working part-time (before-after-comparison) or on a control group consisting of persons who do not work.

- The major drawback of the before-and-after comparison lies in the assumption (12) (denoting by t_0 an earlier grade before working part-time and t_1 a year when the student is/was working part-time). Since students are learning and develop with progressing time, the earlier outcome of a part-time student is not a suitable control outcome to which we can contrast the effect of part-time work. Hence this assumption is bound to be violated.

$$\text{(12)} \qquad \mathrm{E}(YC_{t_0}|D = 1) = \mathrm{E}(YC_{t_1}|D = 1)$$

- At the same time, workers and non-workers differ in characteristics that are likely to influence the outcome variable, and therefore we cannot identify the counterfactual with the mean outcome of non-working individuals

$$\text{(13)} \qquad \mathrm{E}(YC|D = 1) \neq \mathrm{E}(YC|D = 0)$$

6.3 Controlling for selection on observable characteristics : a matching approach

6.3.1 Conditional Independence Assumption

In our work, we refer to a Conditional Independence Assumption (CIA) which implies that we can estimate the average non-working outcome based on the population of non-workers as long as they have the same observable characteristics X as the working students. Under the CIA, one gets

$$\text{(14)} \qquad \mathrm{E}(YC|D = 1, X) = \mathrm{E}(YC|D = 0, X)$$

indicating that working group and the non-working group are comparable conditional on X. In order to correct for selection bias based on observable characteristics we implement a statistical matching approach. Matching is widely used in the empirical social sciences in order to keep boundary conditions constant in causal analysis. In the context of evaluation studies matching approaches produce a comparison group that resembles the participating group with respect to the observable characteristics, which in this context might be understood as the boundary conditions. Under the Conditional Independence Assumption, the average effect of treatment-on-the-treated for the population of working students can be estimated by

$$\text{(15)} \qquad \frac{1}{N} \sum_{i \in \{D=1\}} \left(YT_{i,t} - \sum_{j \in \{D_t=0\}} w(i,j) YC_{j,t} \right)$$

where $YT_{i,t}$ is the outcome of a working student $i \in \{D = 1\}$, $YC_{j,t}$ the outcome for non-working students $j \in \{D_t = 0\}$ in grade t. For reasons of simplicity, we omit index t in the following. Then, we estimate the non-work outcome of an individual working students by implementing a weight function $w(i, j)$ in the sample of the non-working students relative to the observable characteristics X of each individual i. This weight function gives a higher weight to non-working students with high similarity to the X of the local working student and a lower weight to persons with only low similarity in X. According to this weight function, the non-work scores for each working student $i \in \{D = 1\}$ are estimated based on the sample of non-workers, with weights summing up to one:

$$\sum_{j \in \{D_t = 0\}} w(i, j) = 1 \tag{16}$$

6.3.2 Kernel matching

In this paper, we apply kernel matching estimators with local linear regression which turned out to be as powerful as nearest neighbour estimators with respect to selection-on-observables bias, based on experimental evidence (Heckman, Ichimura, Todd 1998).[4] Kernel matching implements weight functions for the whole sample of non-workers in order to construct the potential non-working outcome for any working student. The weight function for this estimator down-weights distant observations from the characteristics X_i of a local working student (see Fan (1993)). The potential outcome is estimated in a local linear regression at i on the basis of a weighted average of *all* non-working individuals $j \in \{D = 0\}$.

The weights depend on the deviation of observable characteristics $(X_k - X_i)$ with a sum of the weights equal to one. This results in estimating a weighted least squares estimation regression:

$$\sum_{k \in \{D=0\}} \{YC_k - m - \beta(X_k - X_i)\}^2 \, K\left(\frac{X_k - X_i}{h}\right) \tag{17}$$

where OLS minimizes with respect to m and β and h is a bandwidth parameter. The estimated parameter $\widehat{m}$ then just represents the non-work outcome. The kernel function throughout the paper is specified as a Gaussian kernel with

$$K(\varphi) = \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{1}{2}\varphi^2\right) \quad \text{with} \quad \varphi = \left(\frac{X_j - X_i}{h}\right) \tag{18}$$

[4]The main reason for the use of kernel matching is the failure of Bootstrap techniques in order to obtain robust inference for the estimated work effect when using nearest neighbour matching (see Abadie and Imbens 2005).

Härdle (1990) concluded that the choice of the bandwidth - and not the choice of kernel function - is crucial for the performance of the nonparametric fit. The bandwidth determines how fast the weights decrease as the distance from X_i increases and thus controls the smoothness of the resulting estimate. There is no "golden rule of bandwidth selection". Pagan and Ullah (1999) discuss that if h is chosen high, the variance of the estimated parameters is quite low as a large number of points are used for the estimation. A small bandwidth h gives fragile density estimates and locally, only few points are included in the estimation, so that the variance increases, but less bias is produced. The trade-off between variance and bias is especially important in our application because selection bias is to be minimised. With respect to selection bias based on observable characteristics, we should rather tend to an under smoothing than to have a too high value of h. An option quite often used is the application of Silverman's Rule of Thumb (ROT). As an optimal bandwidth selection for a Gaussian kernel, Silverman (1986) gives the following recommendation, on which we rely in the paper

$$h_{ROT} = 0.9A \cdot n^{-1/5} \tag{19}$$

where h is the selected bandwidth and $A = \min(std, iqr/1.34)$, std the standard deviation, iqr the interquartile range of the sample, and n is the total sample size.

6.3.3 Implementing Propensity Score Matching

Consider X to consist of a vector of many observable characteristics. Then a disadvantage of matching is the "curse-of-dimensionality" with respect to all dimensions of X. Therefore, this paper follows the result of Rosenbaum and Rubin (1983) that the CIA in equation (14) also holds with respect to the *probability of working as a student* (propensity score) $P(X)$ as a function of the observable characteristics X, i.e.

$$\mathrm{E}(YC|D = 1, P(X)) = \mathrm{E}(YC|D = 0, P(X)) \tag{20}$$

The propensity score allows a matching based on a one-dimensional probability. This dimension-reduction diminishes the problem of finding adequate matches and the problem of empty cells. However, propensity matching comes at the costs that the propensity score has to be estimated itself.

We estimate the propensity score as a parametric probit model following the standard approach used in the literature. The probit model of the propensity score estimates the probability of working as a student depending on observable covariates. In this model, the decision to work as a student depends on a number of observable characteristics that can be observed for both groups.

As previously discussed, these covariates should ideally include all important variables influencing the individual decision to work or not. Fortunately, we are able to access a large number of observable characteristics from the NELS88 dataset. We have earlier provided some descriptives for the covariates used in estimating the propensity score. Using the "standard" individual, socio-economic, family background, school level and regional variables as outlined in the literature (Lillydahl, 1990; Schoenhals and Tienda, 1998; Tyler, 2003; Warren *et al*, 2000) as well as school level information, we estimate the propensity score. [5]

Propensity score matching can only be successful concerning the conditioning on observable characteristics if the estimated propensity scores of working students and non-working students overlap sufficiently. We implement a common support requirement which led to the discarding of three cases who were outside the common support region. Finally, after matching, all observable characteristics should be balanced between working students and matched comparison observations. The sample of working students and merged control observations should show the same distribution of observable characteristics. We formally test on the significance of differences in observable characteristics between the sample of working students and the matched control outcomes using t-tests. If the means of the two groups are statistically different from each other with respect to the observable X, the t-test will indicate a failure of the matching. Results indicate that propensity score matching was successful in balancing all observed covariates between workers and matched controls. The only exception was for the variable gender. We therefore decide to stratify the regressions by gender and report both male and female results.[6]

6.4 Controlling for unobservable individual characteristics

6.4.1 Difference-in-differences

Most econometric literature makes use of the assumption that selection bias due to observable characteristics and selection bias due to unobservable characteristics can be considered separately (Heckman, Ichimura and Todd 1998). While matching estimators as well as other solutions on selection bias due to

[5] An example of the propensity score estimation can be found in a complementary file. Additional information is available upon request.

[6] We are happy to provide additional detail regarding the balancing properties on request.

observable characteristics cope with the influence of measured variables on the participation decision, selection bias due to unobservable characteristics has to be dealt with differently.

To account for selection of unobservables, the empirical literature has pursued various strategies, in particular difference-in-difference estimators (see Heckman, LaLonde and Smith, 1999). Such an approach requires panel data and builds on the assumption of time-invariant linear selection effects. This estimator extends simple before-after comparisons to determine the treatment effect based on the presumption that the outcome variable can also change over time due to reasons unrelated to the decision to work. Here, we implement a "conditional difference-in-differences estimator" (cDiD), where conditional means that working students are already matched to an appropriate non-working outcome conditional on X.[7]

While the static cDiD-estimator is also based on the assumption of time-invariant linear selection effects, we extend this cDiD estimator by implementing it as a random growth model controlling for individual time trends. A previous application of such an extended cDiD estimator can be found in Dorsett (2005) and we follow the implementation proposed there.

6.4.2 Conditional difference-in-differences in matched samples

In the following, we model the conditional difference-in-differences estimator within a regression framework. The implementation of this model requires matched samples of working students and the estimated non-working outcomes for this population for two or more consecutive points in time. The NELS panel data provide information about test scores in Mathematics and English language for three grades (8, 10 and 12) and allow an appropriate implementation of this identification strategy. The basic set-up of the data is as follows:

Y_i	is the test score for a working student or a matched control
$D_i \in \{0, 1\}$	is the working status of the student (1 if part-time work)
D_s	is a dummy variable for the time period s, $D_s = 0$ for all periods other than s

The conditional difference-in-differences approach assumes that working students can be observed for at least two periods ($s \in \{t', t\}$, with $t' < t$) and that there are matched outcomes of students not working during grade 12 which are observed in these two periods.

[7] Heckman, Ichimura, Smith and Todd (1998) were the first to use cDiD estimators.

Since we analyse the effects of part-time working on students performance in grade 12, part-time work takes place between the results obtained in grade 10 and the results of grade 12, $t' < k < t$. In the period before t' we observe the following:

$$Y_{it'} = \beta_0 + \beta_D D_i + \varepsilon_{it'}$$

At the end of grade 12 in period t we observe the base effect of grade 10 and additionally an effect of working in grade 12. For the second period, the model shows:

$$Y_{it} = \beta_0 + \beta_D D_i + \beta_t D_t + \beta_2 D_i + \varepsilon_{it}$$

where β_D is the differential effect caused by either work (the sample of working students) or non-work (the estimated non-working outcomes of the working students based on the matching approach), β_t is a common trend of both the outcome of the working students and the matched non-working outcome. Finally, β_2 shows the effect of working in grade 12. The most important assumption of this model is that both groups (working students and matched non-working students) show the same general movement in their test scores over time.[8] The working-effect can then be estimated in a stacked panel data set:

$$Y_i = \beta_0 + \beta_D D_i + \beta_t D_t + \beta_2 D_i D_t + \varepsilon_i \tag{21}$$

The effect of the treatment-on-the-treated can be estimated by the parameter estimate of an interaction of the dummy variable indicating the working status during grade 12 and the indicator of the time period under consideration, i.e. grade 12. The estimated effect is β_2. In analogy, the effect estimated by β_2 corresponds exactly to the difference-in-differences in means between working students and matched controls given as:

$$\frac{1}{N} \sum_{i \in \{D=1\}} \left(YT_{i,t} - YT_{i,t'} - \left[\sum_{j \in \{D=0\}} w(i,j) YC_{j,t} - \sum_{j \in \{D=0\}} w(i,j) YC_{j,t'} \right] \right) \tag{22}$$

The estimation as a regression model required the assumption that ε_i is a normally distributed random

[8]It is also known as the parallel trend assumption.

variable with mean zero.[9]

6.4.3 Considering pre-programme differences

The estimation of the model in periods before the students were working should not show any significant differences between the working students and the matched non-working outcome. This model can therefore be estimated for the earlier years included in the panel (i.e. grades 8 and 10), when the treated students were not yet working or only a part of them was working (this makes the estimator a bit unattractive). Implementing the difference-in-differences estimator in a matched sample of individuals who are working during grade 12 and control outcomes in these periods before the time period under consideration

$$s \in \{t'', t'\} \text{ with } t'', t' < k$$

should not show any significant difference due to the later status of being a working student, otherwise the model would be specified incorrectly and the identifying assumption of the cDiD estimator would be violated. Therefore, the estimated coefficient β_2 must not be significantly different from zero.

If this preprogramme test fails, the application of a random growth model allows for a generalisation of the cDiD model. A random growth model no longer requires the differences between the working students and the matched control outcome to follow a common trend. Both outcomes can now follow group specific trends over time. If the preprogramme test reveals differential trends between both groups even before grade 12, these group specific trends are extrapolated into the later period under the assumption that they remain stable for both groups - but trends may be different across groups. Therefore, the random growth model has less restricted assumptions about the difference between both workers and non-workers (or the matched non-working sample), allowing for differences in the development over time.

The modeling of the random growth model requires three time periods, and we make use of all information for grade 8, 10 and 12 available from the NELS data. As before, we consider matched samples between working and non-working students in three periods, so that

$$s \in \{t, t', t''\}, \text{ where } t'' < t'$$

[9] $\varepsilon_i = D_{t'}\varepsilon_{it'} + D_t\varepsilon_{it}$

The period of interest is k with $t' < k < t$ and we estimate the effect of part-time working during grade 12 on test scores. In the first period, grade 8, workers and matched controls should show the following outcome on their test scores, as above:

$$Y_{it''} = \beta_0 + \beta_D D_i + \varepsilon_{it''}$$

In the second period before the work effect of grade 12, i.e. in grade 10, the model allows the estimation of a second preprogramme result of working part-time. This preprogramme outcome might be different not only because of the common trend β_t, but also because of a possible differential trend that affects working students and matched controls differently:

$$Y_{it'} = \beta_0 + \beta_D D_i + \beta_t D_t + \beta_1 D_i + \varepsilon_{it'}$$

Thus, while β_t shows the common trend of both groups, the random growth approach allows to model a differential trend for the working group, namely β_1. In the third period, i.e. in grade 12, the model finally shows the outcome of the treatment, the common trend and the differential trend:

$$Y_{it} = \beta_0 + \beta_D D_i + 2\beta_t D_t + 2\beta_1 D_i + \beta_2 D_i + \varepsilon_{it}$$

In grade 12, both the common trend as well as the differential trend increase by one increment. The last term shows the differential effect in the third period that should reveal a treatment effect free from common and differential trends of both groups. β_2, should be an estimate of this treatment effect once the model is implemented in a regression framework of the following form:

$$Y_i = \beta_0 + \beta_t(D_{t''} + 2D_t) + \beta_1(D_{t''} D_i + 2D_t D_i) + \beta_2 D_t D_i + \varepsilon_i \tag{23}$$

7 Results

Tables 3 to 6 present the results for different types of part-time work (measured by intensity and occupation), where part-time working individuals (the treatment group) are compared to non-working individuals (the control group). Estimates in Tables 3 and 4 assume that working in grade 12 could have effect on test scores in grade 12, regardless of work status in previous years. In other words, working in grade 12 is a separate and independent treatment which can only occur in grade 12. However, if one assumes that working in grade 10 influences test score in grade 12 (i.e. can be considered as part of the treatment effect), then the difference-in-differences methodology breaks down. This may occur if one assumes that working *per se* is the actual treatment of interest, rather than working *in grade 12*. We therefore also condition the analysis on not having worked in grade 10. These results are presented in Tables 5 and 6.

Table 3 presents the results for working in grade 12. Simple propensity score matching differences suggest that females who hold a part-time job in grade 12 experience a statistically significant negative effect on standardized math scores. However, this effect is fairly small. Being female and working in grade 12 is associated with a lower test score by -0.46 points. Working in grade 12 does not appear to result in a lower reading score for females. For males we find that working in grade 12 is associated with a higher reading score of 0.42 test score points. There is no significant effect on math score for males.

Such results are interesting as they suggest differential effects of working during school not just by gender, but also by subject. However, examining the conditional difference-in-differences estimates we find that all coefficients now become statistically insignificant. Such results suggest that once we control for unobservable time invariant characteristics, all effects of working part-time disappear. Hence previous estimates, whilst controlling for all observable characteristics, failed to take into account unobserved heterogeneity among individuals and as such, "falsely" prescribed a treatment effect to working. Once controlled for, any effect of working in grade 12 disappears, suggesting that working in grade 12 has no significant causal impact on educational attainment. Whilst we offer different definitions of working in grade 12, this is a story which repeats itself throughout the results and can be taken as the main result from this analysis.

Continuing to examine Table 3 for differences in the amount of hours worked per week in grade 12, we find that there is no statistically significant affect, for both males and females, from working 0 to 10 hours per week. We find that as the intensity increases, propensity score matching estimates report a significant effect of working 11 to 20 hours for males on reading scores (0.67). Working 21 hours or more has a significant negative impact on female math (-0.70) and reading scores (-0.88). However, all difference-in-differences estimates become statistically insignificant. The insignificant results in the difference-in-differences estimation imply no need for a random growth model, however, we have included them for completeness.

Part-time work effect for women, job definition 1
Anyone who has a part-time job in grade 12
Evaluation outcomes

	Females			*Males*		
	Coef.	S.E.	Sign.	Coef.	S.E.	Sign.
Math, simple	-0.46^{**}	0.16	0.00	-0.13	0.17	0.46
Read, simple	-0.19	0.15	0.21	0.42^{**}	0.17	0.01
Math, DID	-0.29	0.22	0.20	-0.13	0.24	0.60
Read, DID	-0.29	0.22	0.19	0.22	0.24	0.35
Math, RG	-0.35	0.40	0.38	-0.17	0.43	0.68
Read, RG	-0.49	0.39	0.21	-0.08	0.42	0.85

Part-time work effect for women, job definition 3
Anyone who has a part-time job in grade 12
and works 11 to 20 hours per week
Evaluation outcomes

	Females			*Males*		
	Coef.	S.E.	Sign.	Coef.	S.E.	Sign.
Math, simple	-0.34	0.24	0.15	0.16	0.27	0.55
Read, simple	-0.09	0.22	0.71	0.67^{*}	0.28	0.02
Math, DID	-0.22	0.33	0.50	0.06	0.39	0.88
Read, DID	-0.02	0.32	0.95	0.42	0.40	0.28
Math, RG	-0.29	0.59	0.62	0.02	0.69	0.98
Read, RG	0.05	0.57	0.93	0.10	0.69	0.89

Part-time work effect for women, job definition 2
Anyone who has a part-time job in grade 12
and works 0 to 10 hours per week
Evaluation outcomes

	Females			*Males*		
	Coef.	S.E.	Sign.	Coef.	S.E.	Sign.
Math, simple	0.26	0.38	0.49	0.01	0.32	0.97
Read, simple	0.44	0.38	0.24	0.05	0.31	0.87
Math, DID	-0.08	0.53	0.88	-0.01	0.46	0.99
Read, DID	-0.11	0.53	0.84	-0.21	0.44	0.63
Math, RG	-0.39	0.95	0.68	0.08	0.82	0.93
Read, RG	-0.67	0.93	0.47	-0.47	0.79	0.56

Part-time work effect for women, job definition 4
Anyone who has a part-time job in grade 12
and works 21 or more hours per week
Evaluation outcomes

	Females			*Males*		
	Coef.	S.E.	Sign.	Coef.	S.E.	Sign.
Math, simple	-0.70^{*}	0.31	0.02	$-0.50^{\dagger}$	0.29	0.09
Read, simple	-0.88^{**}	0.31	0.00	0.32	0.29	0.28
Math, DID	-0.35	0.44	0.42	-0.35	0.42	0.40
Read, DID	-0.97	0.65	0.14	0.27	0.41	0.52
Math, RG	0.06	0.77	0.94	-0.25	0.73	0.73
Read, RG	-0.96	0.77	0.21	0.01	0.72	0.99

Significant at: † 10%, * 5%, ** 1%.

Table 3: Estimation of the effect of part time work unconditional to work at grade 10

Turning to Table 4, where we examine different forms of occupation and weekend work, we find that none of the conditional difference-in-differences estimates are statistically significant. Whilst there is some suggestion in simple differences estimates that working in the "mainstream" work categories (grocery clerk, fast food and salespersons) is slightly less detrimental for women and slightly more beneficial for males, difference-in-differences estimates suggest that such significant results can be explained away by considering previous test score movements.

Examining Table 5 and 6, where we condition on *not* having worked part-time in grade 10, we find that, generally speaking, most of the estimates are very similar to the previous results where we do not condition on previous work experience. Matching simple differences suggest that females now experience a higher detrimental effect on reading and math scores from working more than 21 hours (-1.61 and -1.05 respectively). However, like the previous estimates, no significance is detected in the difference-in-differences estimates, again suggesting that once unobserved heterogeneity is taken into account, any direct effect between working during high school and test scores disappears.

8 Conclusion

This paper attempts to contribute to the literature regarding the effect of working during school on several grounds. Firstly, using models from the evaluation literature, we control for sample selection on observables by using propensity score matching estimators. Furthermore, we control for unobserved

Part-time work effect for women, job definition 5
Anyone who has a part-time job in grade 12
but does not work as a babysitter, lawn or household worker
Evaluation outcomes

	Females Coef.	S.E.	Sign.	*Males* Coef.	S.E.	Sign.
Math, simple	-0.46**	0.17	0.01	-0.11	0.17	0.53
Read, simple	-0.31*	0.16	0.05	0.43**	0.17	0.01
Math, DID	-0.19	0.24	0.42	-0.10	0.25	0.68
Read, DID	-0.25	0.23	0.28	0.22	0.25	0.38
Math, RG	-0.14	0.42	0.74	-0.15	0.44	0.74
Read, RG	-0.32	0.41	0.44	-0.09	0.43	0.84

Part-time work effect for women, job definition 7
Only those who have a part-time job in grade 12
and increased their work hours from grade 10
Evaluation outcomes

	Females Coef.	S.E.	Sign.	*Males* Coef.	S.E.	Sign.
Math, simple	-0.69*	0.33	0.03	0.06	0.29	0.83
Read, simple	-0.23	0.31	0.46	-0.10	0.30	0.74
Math, DID	-0.39	0.46	0.40	-0.31	0.42	0.46
Read, DID	-0.09	0.44	0.84	-0.50	0.43	0.25
Math, RG	-0.22	0.82	0.79	-0.74	0.74	0.32
Read, RG	-0.15	0.79	0.85	-1.12	0.74	0.13

Part-time work effect for women, job definition 6
Only those who have a part-time job in grade 12
and are salespersons, fast food workers or grocery clerks
Evaluation outcomes

	Females Coef.	S.E.	Sign.	*Males* Coef.	S.E.	Sign.
Math, simple	-0.33	0.22	0.13	0.17	0.27	0.52
Read, simple	-0.36†	0.21	0.09	0.81**	0.26	0.00
Math, DID	-0.21	0.31	0.50	-0.05	0.38	0.89
Read, DID	-0.31	0.30	0.30	0.10	0.38	0.80
Math, RG	-0.25	0.55	0.65	-0.33	0.67	0.62
Read, RG	-0.36	0.54	0.51	-0.71	0.66	0.28

Part-time work effect for women, job definition 8
Only those who work weekends only in grade 12
Evaluation outcomes

	Females Coef.	S.E.	Sign.	*Males* Coef.	S.E.	Sign.
Math, simple	-0.10	0.38	0.79	0.15	0.41	0.71
Read, simple	0.15	0.36	0.68	0.43	0.41	0.30
Math, DID	0.12	0.54	0.82	-0.07	0.57	0.91
Read, DID	-0.24	0.52	0.65	-0.27	0.58	0.65
Math, RG	0.30	0.98	0.76	-0.24	1.02	0.81
Read, RG	-0.69	0.93	0.46	-1.02	1.01	0.32

Significant at: † 10%, * 5%, ** 1%.

Table 4: Estimation of the effect of part time work unconditional to work at grade 10: decomposition by type of work

Part-time work effect for women, job definition 1
Anyone who has a part-time job in grade 12
Evaluation outcomes

	Females Coef.	S.E.	Sign.	*Males* Coef.	S.E.	Sign.
Math, simple	-0.54*	0.23	0.02	-0.40	0.28	0.15
Read, simple	-0.31	0.22	0.16	-0.28	0.28	0.32
Math, DID	-0.33	0.32	0.32	-0.19	0.40	0.63
Read, DID	-0.33	0.32	0.30	-0.06	0.40	0.88
Math, RG	-0.17	0.57	0.77	-0.08	0.69	0.90
Read, RG	-0.37	0.56	0.51	-0.10	0.69	0.88

Part-time work effect for women, job definition 3
Anyone who has a part-time job in grade 12
and works 11 to 20 hours per week
Evaluation outcomes

	Females Coef.	S.E.	Sign.	*Males* Coef.	S.E.	Sign.
Math, simple	-0.44	0.35	0.21	-0.30	0.47	0.53
Read, simple	-0.11	0.34	0.75	-0.04	0.48	0.94
Math, DID	-0.49	0.49	0.32	-0.13	0.67	0.84
Read, DID	-0.16	0.48	0.74	-0.18	0.68	0.80
Math, RG	-0.51	0.87	0.56	-0.05	1.16	0.97
Read, RG	-0.07	0.85	0.94	-0.54	1.18	0.65

Part-time work effect for women, job definition 2
Anyone who has a part-time job in grade 12
and works 0 to 10 hours per week
Evaluation outcomes

	Females Coef.	S.E.	Sign.	*Males* Coef.	S.E.	Sign.
Math, simple	-0.23	0.45	0.62	-0.03	0.58	0.96
Read, simple	-0.19	0.44	0.67	-0.30	0.59	0.62
Math, DID	-0.13	0.65	0.85	-0.25	0.83	0.77
Read, DID	-0.10	0.63	0.88	-0.61	0.84	0.47
Math, RG	-0.09	1.16	0.94	-0.42	1.48	0.77
Read, RG	-0.09	1.13	0.94	-0.98	1.47	0.50

Part-time work effect for women, job definition 4
Anyone who has a part-time job in grade 12
and works 21 or more hours per week
Evaluation outcomes

	Females Coef.	S.E.	Sign.	*Males* Coef.	S.E.	Sign.
Math, simple	-1.61**	0.45	0.00	-0.38	0.50	0.44
Read, simple	-1.05*	0.45	0.02	0.20	0.50	0.69
Math, DID	-0.54	0.64	0.40	-0.28	0.71	0.70
Read, DID	-0.96	0.65	0.14	0.29	0.70	0.68
Math, RG	-0.03	1.11	0.98	-0.23	1.22	0.85
Read, RG	-1.34	1.13	0.24	0.21	1.20	0.86

Significant at: † 10%, * 5%, ** 1%.

Table 5: Estimation of the effect of part time work conditional on not working in grade 10

Part-time work effect for women, job definition 5
Anyone who has a part-time job in grade 12
but does not work as a babysitter, lawn or household worker
Evaluation outcomes

	Females			*Males*		
	Coef.	S.E.	Sign.	Coef.	S.E.	Sign.
Math, simple	-0.55*	0.24	0.02	-0.42	0.29	0.14
Read, simple	-0.31	0.23	0.19	-0.29	0.29	0.32
Math, DID	-0.36	0.34	0.29	-0.17	0.41	0.67
Read, DID	0.10	0.35	0.77	-0.05	0.41	0.89
Math, RG	-0.21	0.60	0.72	-0.05	0.71	0.95
Read, RG	-0.48	0.59	0.41	-0.08	0.70	0.90

Part-time work effect for women, job definition 7
Only those who have a part-time job in grade 12
and increased their work hours from grade 10
Evaluation outcomes

	Females			*Males*		
	Coef.	S.E.	Sign.	Coef.	S.E.	Sign.
Math, simple	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.
Read, simple	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.
Math, DID	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.
Read, DID	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.
Math, RG	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.
Read, RG	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.

Part-time work effect for women, job definition 6
Only those who have a part-time job in grade 12
and are salespersons, fast food workers or grocery clerks
Evaluation outcomes

	Females			*Males*		
	Coef.	S.E.	Sign.	Coef.	S.E.	Sign.
Math, simple	-0.28	0.32	0.38	-0.15	0.44	0.73
Read, simple	0.17	0.31	0.58	-0.03	0.45	0.94
Math, DID	-0.57	0.45	0.21	-0.16	0.63	0.80
Read, DID	0.06	0.46	0.90	-0.26	0.64	0.69
Math, RG	-0.46	0.80	0.57	-0.31	1.09	0.78
Read, RG	-0.45	0.78	0.57	-0.88	1.11	0.43

Part-time work effect for women, job definition 8
Only those who work weekends only in grade 12
Evaluation outcomes

	Females			*Males*		
	Coef.	S.E.	Sign.	Coef.	S.E.	Sign.
Math, simple	-0.22	0.57	0.70	-0.66	0.69	0.33
Read, simple	0.27	0.52	0.61	0.07	0.70	0.92
Math, DID	0.02	0.81	0.98	-0.53	0.96	0.58
Read, DID	0.18	0.82	0.83	-0.86	0.99	0.38
Math, RG	0.26	1.45	0.86	-0.77	1.70	0.65
Read, RG	-0.14	1.37	0.92	-1.98	1.72	0.25

Significant at: † 10%, * 5%, ** 1%.

Table 6: Estimation of the effect of part time work conditional on not working in grade 10: decomposition by type of work

heterogeneity by using difference-in-difference methods. Results indicate that, once such factors are controlled for, we find no significant evidence of working by the end of high school (grade 12) affecting math or reading scores.

In line with most of the recent papers estimating the impact of part-time work on educational attainment, our analysis suggests that OLS results are biased because of a selection on unobservables. While some detrimental effect of part time work can be found when controlling for differences in observable characteristic in a flexible non parametric way, no significant effect remains when we also control for differences in unobservable characteristics using conditional difference in differences. Besides, our identification strategy does not rely on the validity of the choice of instrumental variables. Thus, our approach could be more robust than previous studies instrumenting part-time work decisions to correct for endogeneity.

In conclusion, we find that the causal effect on educational attainment of working during grade 12 in high school is negligibly small. Considering that we do not find a significant relationship between hours worked and standardized test scores in grade 12, we argue that the "zero-sum model" may not be as applicable in explaining the relationship between working part-time and education as it is often assumed. Furthermore we find no evidence of different job types significantly influencing reading and mathematics score. This suggests that the "socialisation" based arguments, which predict that working may complement education, are also less persuasive than previously thought.

The fact that once unobservable characteristics are controlled for, we obtain significantly different results compared to simple matching estimates (in this case non-significant results) indicates that Warren's (2002) primary orientation approach is an attractive option in explaining relationship between working and schooling. The negative association which is sometimes found between educational attainment and part-time work is unlikely to transmit itself through working *per se*, but through unobservable characteristics: our results show that these part-time working individuals have, every observed characteristics being equal, a lower propensity for educational attainment[10]. One could thus argue that stricter child labor laws are unlikely to be conductive in achieving higher attainment scores and that, as regards educational attainment, working during high school should be neither encouraged nor discouraged.

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[10]Among others, this may stem from a lower unobserved ability or motivation for schooling.

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