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

Franz Buscha†, Arnaud Maurel‡, Lionel Page§ and Stefan Speckesser¶

†*University of Westminster, Westminster Business School, 35 Marylebone Road, London NW1 5LS, UK (e-mail: buschaf@wmin.ac.uk)*
‡*Department of Economics, Duke University, 213 Social Sciences Durham NC 27708-0097, USA; CREST and IZA (e-mail: arnaud@amaurel.net)*
§*Queensland University of Technology, School of Economics and Finance, GPO Box 2434, Brisbane QLD 4001, Australia (e-mail: lionel.page@qut.edu.au)*
¶*Institute for Employment Studies, Sovereign House, Church Street, Brighton BN1 1UJ, UK (e-mail: stefan.speckesser@employment-studies.co.uk)*

Abstract

Using American panel data from the National Education Longitudinal Study of 1988, this article investigates the effect of working during grade 12 on attainment. We employ, for the first time in the related literature, a semiparametric propensity score matching approach combined with difference-in-differences. We address selection on both observables and unobservables associated with part-time work decisions, without the need for instrumental variable. Once such factors are controlled for, little to no effects on reading and math scores are found. Overall, our results therefore suggest a negligible academic cost from part-time working by the end of high school.

I. Introduction

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 US education system is remarkably high. It was here that some of the first questions about the effect of working during school on attainment 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 can be seen as a substitute to education because any additional increase

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in time spent working leads, *ceteris paribus*, to a reduction in time spent on education.[1] 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, 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). Most of the existing studies show that working particularly long hours during school has a detrimental impact on educational attainment (Greenberger *et al*., 1980; Marsh, 1991; Eckstein and Wolpin, 1999; Stinebrickner and Stinebrickner, 2003; Tyler, 2003). 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 (Steinberg *et al*., 1982; Lillydahl, 1990; Oettinger, 1999; Montmarquette, Viennot-Briot and Dagenais, 2007). In these studies, there is an approximate inflection point varying between 10 and 20 hours of work per week.

On an empirical ground, the main difficulty in identifying and thus estimating the causal effect of part-time work on educational attainment lies in the potential endogeneity of part-time work. Indeed, labour supply decisions of students are likely to be related to unobserved characteristics that are in turn related to academic attainment. For instance, conditional on observables, students deciding to work part-time may have a lower unobserved ability or motivation for schooling. In that case ordinary least square (OLS) estimates would overstate any detrimental effect of part-time work.

Recent literature revolves strongly around correctly accounting for unobserved individual heterogeneity within part-time work decisions. While articles by Eckstein and Wolpin (1999) and Montmarquette *et al*. (2007) rely on a structural approach to estimate the effect of working on educational attainment, most of the articles hinge on the availability of an instrument for part-time labour supply (Stinebrickner and Stinebrickner, 2003; Tyler, 2003; Dustman and van Soest, 2007; Rothstein, 2007).

However, as already pointed out by Stinebrickner and Stinebrickner (2003), an instrument causing an exogenous variation of part-time work decisions is very difficult to find in this context. Up to now, even the best attempts to provide such an exogenous variation are questionable. Using US interstate variations in child labour laws as an instrument for students' labour supply, as is done by Tyler (2003), might not be valid, since the adoption of specific child labour laws within a state might be related to the emphasis placed on educational attainment and therefore be also endogenous with respect to academic attainment.[2]

Besides, even when the instrument is truly exogenous, the Instrumental Variable (IV) estimates at best a weighted average of the local average treatment effect parameters (LATE; Imbens and Angrist, 1994). In that context, the LATE parameters correspond to the average effects of part-time work for specific subpopulations of individuals whose number of hours worked is affected by the instrument (e.g. the pupils for whom child

[1] This argument is usually referred to as the zero-sum model in the literature.

[2] Given the widely spread belief of an adverse impact of part-time work on educational attainment, it might be that a state placing greater emphasis on academic attainment (with, e.g. a better school quality) would adopt more stringent child labour laws.

labour laws are binding in the case of Tyler, 2003). In the presence of heterogeneous part-time work effects on educational attainment, this questions the external validity of these results.[3]

In this article, relying on the National Education Longitudinal Study of 1988 (NELS:88) dataset, we address such issues using non-experimental estimators, which do not rely on the validity of an instrument to estimate the causal effect of part-time work during grade 12 on educational attainment by the end of grade 12.[4] We take advantage of both the longitudinal nature of the NELS:88 and the richness of the available set of covariates by employing, for the first time in the related empirical literature, a semiparametric propensity score matching approach combined with difference-in-differences (conditional difference-in-differences, CDiD; Heckman *et al.*, 1998). We further allow differential trends in attainment over time according to the working status in grade 12, by relying on a matching approach combined with difference-in-difference-in-differences (conditional difference-in-difference-in-differences, CDiDiD). By doing so, we are able to address selection on both observables and unobservables associated with labour supply decisions of students, and consistently estimate the average treatment effect on the treated.[5] Once observable and unobservable factors are controlled for, we find little to no effects on 12th grade standardized reading and math scores, even for intensive part-time employment.

The remainder of this article is set out as follows. In section II, we briefly present stylized facts about part-time work during schooling in the United States. Section III provides a brief overview of the NELS:88 as well as sample descriptive statistics. Section IV details the empirical analysis while section V presents the results. Finally section VI concludes.

II. 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 years.[6] Even those below the minimum legal working age may find part-time employment in informal 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 labour market, and therefore, one cannot separate the education and the labour market completely.

The Youth Labor Force 2000 report, by the American Bureau of Labor Statistics, finds that during the 1996–98 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 prevalence of part-time work 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%)

[3] See Heckman (2001) for a survey on the evidence on heterogeneous treatment effects.

[4] In the United States, grade 12 is the last year of high school, which corresponds to the 12th school year after kindergarten. In the article, we consider the effect of working part-time during grade 12 on schooling performances by the end of the same grade. We leave for further research the estimation of potential medium or long-term part-time work effects on attainment.

[5] A closely related methodological approach has recently been followed on the same dataset by Sanz-de-Galdeano and Vuri (2007) who use a DiD estimator to assess the effect of divorce on students' academic performances. Our identification strategy differs from theirs in that it relies on a more flexible semiparametric matching approach to control for the observable characteristics of the individuals.

[6] Note that state-wise variations exist for both the minimum school-leaving age and the minimum working age.

for 14-year olds and to 64% for those aged 15. By age 16–17 over 80% of individuals will have held a part-time job. Furthermore, as children grow older, the nature of work appears to formalize from freelance work into a more mature and binding employment relationship. Evidence from the literature finds similar proportions, and of those who do work, the work intensity is substantial and increasing with age (Ruhm, 1995). Finally, as mentioned by Singh (1998), the proportion of students holding a part-time job has dramatically increased during recent decades: students in the 1990s were twice as likely to work part-time as students in 1950.

Within the policy environment, a dichotomy of views exist. Those holding the view that working is complementary for educational experiences of young adults are in favour of formal school-to-work programmes, with the aim of expanding the employment experience of students. Conversely, those who hold a less favourable view and argue that such programmes are undesirable and counter-productive consider that more stringent child labour laws should be introduced. The view that part-time work has a detrimental effect on educational attainment, relying on academic research, is increasingly widespread in the last 10 years. This view has recently led some states, such as Massachusetts or Colorado, to implement more stringent child labour laws reducing the maximum amount of time students can work during the school year.

III. Data and descriptive statistics

The data used in this article are from the NELS:88 conducted by the US National Center for Education Statistics. It is a nationally representative sample of students who were 8th graders in the base year of 1988. Further follow-up surveys were conducted in 1990 (10th grade), 1992 (12th grade), 1994 and 2000, giving a total of five waves. Making use of the 'public use file 88/92' we have a total set of 27,394 individuals. However, after restricting our analysis to those who are eligible and still in school by grade 12 we are left with 16,663 cases.[7] Missing values for gender reduce this to 15,747 and finally, dropping missing values for part-time work and test scores leaves us with 9,887 individuals.[8]

The NELS:88 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 behaviour of pupils and their success later on. Of special interest for us is the fact that the first three waves of the survey include standardized test scores 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 we choose for educational attainment are the composite

[7]25,851 cases are eligible. Ineligibility arises because of sampling error, language barrier or disability.

[8]Two major selection procedures define our sample: (i) the move from 25,851 respondents to 16,633 because of panel attrition; and (ii) the sub-selection of only 9,887 of these individuals because of missing values. We use NELS:88 second follow-up panel weights to correct for panel attrition. Our weighting scheme is similar to the one used by Warren, LePore and Mare (2000) and Altonji, Elder and Taber (2005) on the same dataset. Finally, we implement a Heckman selection model, which is identified through functional forms given the absence of relevant instruments in the data. The results suggest ignorability of the selection bias induced by missing values in our final sample.

scores of mathematics and reading tests.[9] This choice is motivated by the synthetic nature of these variables, which are likely to take into account the different abilities required from the pupils to succeed in high school.

Furthermore, the NELS:88 survey has detailed questions about the part-time work behaviour of students with information about the intensity of work performed and the occupation. We are able to track the amount of hours worked in grades 8, 10 and 12 (Table 1). We find that the distribution of hours worked 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 and 10 hours per week). However, in 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.[10]

Table 2 provides some descriptive evidence of the relationship between different forms of part-time work and test scores in grade 12. Overall, there appears to be little difference in math and reading scores, whether individuals worked part-time or not. However, a pattern emerges when examining the progression from working few hours per week to many hours per week. For both genders, individuals who work 0–10 hours per week have higher average test scores than individuals who do not work or who work more than 10 hours per week. As the intensity of work increases to 11–20 hours per week, test scores between those who work and do not work converge, and there is little difference between them. Mean scores are much lower for the individuals working 21 hours or more per week. These descriptives support the general finding in the literature concerning the relationship between part-time work and attainment. Those working relatively little appear to have higher test scores whilst those working many hours per week have substantially lower test scores. Finally, examining different forms of part-time work, we do not find substantial differences by excluding those who hold a family-related job (such as babysitters, lawn or household workers) or by examining only those in commercial occupations (such as fast food workers or grocery clerks); although there is a suggestion that those working during weekends only have higher test scores than those who do not. We intend to consider all the proposed part-time work definitions in our estimations as outlined in Table 2.

TABLE 1

Sample proportions (%) of the incidence of work for grades 8, 10 and 12

	Grade 8		*Grade 10*		*Grade 12*	
	Males	*Females*	*Males*	*Females*	*Males*	*Females*
Not working	29.63	31.61	38.43	49.68	34.88	31.96
Working 0–10 hours	55.35	59.45	19.12	19.67	16.16	19.02
Working 11–20 hours	8.23	5.85	19.01	16.63	25.44	31.89
Working 21 or more hours	6.79	3.08	23.43	14.01	24.39	17.14
Number	4,728	5,159	4,728	5,159	4,728	5,159

Source: National Education Longitudinal Study of 1988.

[9]The composite score for reading is based on three different reading tests and for mathematics on five different mathematics tests.

[10]The incidence of work in grade 8 is higher than in grade 10 as a result of the large number of individuals working as babysitters, lawn workers and newspaper deliverers.

TABLE 2

Twelfth grade standardized test scores by type of part-time job (weighted means)

	Male				*Female*			
	Yes		*No*		*Yes*		*No*	
Individuals who have	*Mean*	*SD*	*Mean*	*SD*	*Mean*	*SD*	*Mean*	*SD*
Gr12 Math Score								
PTJ G12	52.59	9.12	53.15	10.24	51.93	8.90	51.21	9.84
PTJ G12 (0–10 hours)	54.28	9.27	52.47	9.52	54.13	8.71	51.10	9.20
PTJ G12 (11–20 hours)	53.52	8.59	52.48	9.82	52.07	8.65	51.55	9.43
PTJ G12 (21 or more hours)	50.22	9.19	53.53	9.46	49.15	8.83	52.28	9.17
PTJ G12 (no family-related work)	52.67	9.14	52.93	10.07	51.98	8.93	51.24	9.62
PTJ G12 (commercial work)	53.01	8.81	52.66	9.79	51.47	8.94	51.87	9.33
PTJ G12 (working weekends only)	54.58	8.83	52.49	9.57	53.75	8.70	51.37	9.22
Gr12 Reading Score								
PTJ G12	51.49	9.25	50.80	10.18	53.31	8.73	52.57	9.42
PTJ G12 (0–10 hours)	53.64	8.92	50.80	9.62	55.66	8.82	52.44	8.85
PTJ G12 (11–20 hours)	51.97	9.17	50.99	9.70	53.29	8.35	53.01	9.21
PTJ G12 (21 or more hours)	49.35	9.15	51.84	9.61	50.69	8.54	53.63	8.94
PTJ G12 (no family-related work)	51.33	9.34	51.17	9.92	53.43	8.76	52.49	9.22
PTJ G12 (commercial work)	52.39	8.72	50.77	9.87	52.74	8.51	53.32	9.18
PTJ G12 (working weekends only)	52.74	9.54	51.04	9.55	55.36	8.84	52.71	8.90

Notes: For males having a part-time job and working between 0 and 10 hours a week, the observed mean score in maths is 54.28; for males not working on a part-time job between 0 and 10 hours a week, the observed mean score in maths is 52.47. PTJ G12, Part-time job in grade 12.

Source: National Education Longitudinal Study of 1988.

IV. Empirical analysis

We contribute to the existing literature by using the panel aspect of the NELS with a CDiD approach as well as its extension exploiting the availability of three time periods (CDiDiD) to control for selection on unobservables associated with part-time work decisions. Besides, 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. Such methods 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 (Heckman, LaLonde and Smith, 1999).[11] Unlike previous articles, our estimation of the work effect relies on a semiparametric local linear matching approach that relaxes the linearity restriction on observables.

Identification issue

Calling YT the working outcome, and YC the non-working outcome, the causal effect of working part-time during 12th grade for those holding a part-time job in grade 12 can be

[11] See, for example Oettinger (1999) and Stinebrickner and Stinebrickner (2003), who use panel data to compute fixed-effects parametric estimates of the part-time work effect on academic achievement.

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 ($YC \mid D=1$). The effect of treatment-on-the-treated is given by:

$$E(YT \mid D=1) - E(YC \mid D=1). \tag{1}$$

In this article, we rely on a matching approach combined first with DiD, and then with DiDiD, to identify the causal effect of part-time work during grade 12 on educational attainment.[12] Basically, matching allows us to build a suitable non-workers control group while forming differences in outcomes over time permits controlling for time-invariant linear selection effects as well as for time trends which are either common across treatment and control groups (DiD) or group specific (DiDiD).

Controlling for selection on observable characteristics: a matching approach

To correct for selection bias based on observable characteristics, we implement a propensity score matching approach. The usual assumption required to estimate what would be the average outcome of working individuals if they were not working is the conditional independence assumption (CIA), which implies, denoting by $P(X)$ the probability of working during grade 12 (propensity score) as a function of observable characteristics X,

$$E(YC \mid D=1, P(X)) = E(YC \mid D=0, P(X)). \tag{2}$$

Under this condition, the average effect of treatment-on-the-treated for the working students population (of size N) can be estimated by

$$\frac{1}{N} \sum_{i \in \{D=1\}} \left(YT_i - \sum_{j \in \{D=0\}} w(i,j) YC_j \right), \tag{3}$$

where YT_i is the outcome of a working student ($i \in \{D=1\}$) and YC_j is the outcome for non-working students ($j \in \{D=0\}$). Then, we estimate the counterfactual non-work outcome of a working individual by implementing a weight function $w(i,j)$ in the sample of the non-working students relative to the predicted propensity score $\widehat{P(X)}$ of each individual i. In this article, we apply Gaussian kernel matching estimators with local linear regression.[13] The counterfactual outcome is estimated in a local linear regression at i on the basis of a weighted average of *all* non-working individuals. We use the modified version of the cross-validation method proposed by Bergemann, Fitzenberger and Speckesser (2009) to estimate the optimal bandwidth for our estimation.

We use a probit model to estimate the propensity score, that is the probability of working during grade 12 depending on observable covariates.[14] In this model, the decision

[12]The CDiD approach was also recently applied by Blundell *et al.* (2004), in the context of the evaluation of a job search assistance programme.

[13]The main reason for the use of kernel matching is the failure of bootstrap techniques to obtain robust inference when using nearest neighbour matching (see Abadie and Imbens, 2008).

[14]Note that we use a bootstrap estimator, with 200 replications, for the standard errors of the estimated treatment effects to capture the estimation error in the propensity score.

to work during grade 12 depends on a number of observable characteristics that can be observed for both groups. These covariates should ideally include all important variables influencing the individual decision to work or not during grade 12. Fortunately, we are able to access from the NELS dataset an unusually rich set of observable characteristics, which are likely to affect the employment status of 12th graders.[15] The results of the probit estimates, according to gender, for the propensity score associated with working part-time during grade 12 are reported in the appendix (Table A1).[16] Propensity score matching can be successful concerning the conditioning on observable characteristics only if the estimated propensity scores of working students and non-working students overlap sufficiently. We implemented 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. We formally test for the significance of differences in observable characteristics between the sample of working students and the matched control outcomes using t-tests. 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 stratify the estimations by gender and report both male and female results.

Controlling for unobservable individual characteristics

To account for selection of unobservables, we implement a CDiD estimator. This method combines a propensity score matching approach with DiD such that, at each period, a counterfactual outcome for the working students at grade 12 if they were not working is estimated semiparametrically. This technique enables us to relax, relative to standard DiD, the linearity assumption when controlling for observables and to control for unobservables exploiting the panel dimension of the data. Besides, Smith and Todd (2005) show that the DID matching estimator performs the best among non-experimental matching-based estimators.

The CDiD estimator is based on the assumption that, conditional on the propensity score, treated and non-treated do not have different time trends relative to their potential outcomes. In the case of different time trends, the estimated effect of the treatment using a CDiD estimator will be biased because of unobservable differences in group dynamics. Typically, a preprogramme test looking at the evolution of the outcomes between grades 8 and 10 would already show a difference in the evolution of the scores of the group of the treated and the untreated *before* the treatment (i.e. working part-time in grade 12) even occurred. To allow differential time trends between treated and non-treated, we also implement a matching approach combined with the DiDiD estimator.

For a treatment which takes place between two periods t' and t with $t > t'$, the required identifying assumption for the CDiD estimator can be represented by an assumption weaker than equation (2) (Heckman *et al.*, 1998):

[15] The set of conditioning variables includes standard individual, socio-economic, family background, school level and regional variables, as well as information on parental education expenditures, school problems including absenteeism, conflicts, alcohol and drugs issues and finally students' educational aspirations at grade 8. As a result of space considerations, detailed descriptive statistics of all covariates have been suppressed. We are happy to provide such a table upon request.

[16] Additional probit results associated with other part-time work definitions are available upon request.

$$E(YC_t - YC_{t'} \mid D=1, P(X)) = E(YC_t - YC_{t'} \mid D=0, P(X)), \tag{4}$$

where YC_t denotes the untreated outcome at period t. The implementation of the CDiD estimator requires matched samples of working and non-working students and the estimated counterfactual non-working outcomes for two or more consecutive points in time.[17] Let $Y_{i,t}$ be the outcome of interest (test score in mathematics or reading) for student i at period t. The CDiD approach assumes that working students can be observed for at least two periods (denoted by t' and t, with $t' = 1990$ and $t = 1992$) and that there are matched outcomes of students not working during grade 12 which are observed in these two periods. Under the identifying assumption made in (4), in the absence of part-time work during grade 12, the average outcome for the treated would have experienced the same variation as the average outcome for the untreated (conditional on the propensity score).[18] Under this assumption, the average effect of the treatment-on-the-treated can be estimated consistently by the DiD in means between working students and matched controls, given as:

$$\frac{1}{N} \sum_{i \in \{D=1\}} \left(YT_{i,t} - YT_{i,t'} - \sum_{j \in \{D=0\}} w(i,j) \left[YC_{j,t} - YC_{j,t'} \right] \right). \tag{5}$$

We also implement a DiDiD estimator with propensity score matching which relies on a weaker identifying assumption. Unlike the CDiD estimator, it is robust to potential differences in outcome trends between treated and untreated as long as these trends are stable over time. The use of a DiDiD model is justified in the context of education because the hypothesis of parallel time trend may be too strong. In the education process, pupils go through an accumulation of knowledge. Arguably, pupils differ not only in terms of level of success but also in terms of ability to progress through time. For this reason, one may consider that the parallel trend assumption must be relaxed to make sure that the results are not biased by the fact that pupils working part-time and pupils not working part-time differ in unobservable characteristics correlated with their ability to progress at school.

We implement this DiDiD estimator, controlling for observable characteristics semi-parametrically by propensity score matching following the same approach as for the CDiD. Supposing the treatment takes place between periods t' and t, with $t > t' > t''$, the identifying assumption is given by:

$$\begin{aligned} E((YC_t - YC_{t'}) - (YC_{t'} - YC_{t''}) \mid D=1, P(X)) \\ = E((YC_t - YC_{t'}) - (YC_{t'} - YC_{t''}) \mid D=0, P(X)). \end{aligned} \tag{6}$$

The average effect of the treatment-on-the-treated in the CDiDiD model will be identified as the change after the treatment in the trend of progression for the outcome of the treated (relative to the matched untreated). The modelling of the DiDiD model requires three time periods, and we make use of 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, namely $t'' = 1988$, $t' = 1990$ and $t = 1992$.

[17]Henceforth, individuals holding a part-time job during grade 12 will be simply referred to as 'working' students.
[18]This is known as the parallel trend assumption.

Finally, under the identifying assumption (6) stated before, the average effect of the treatment-on-the-treated can be estimated consistently by the DiDiD in means between working students and matched controls, which writes:

$$\frac{1}{N}\sum_{i\in\{D=1\}}\left((YT_{i,t}-YT_{i,t'})-(YT_{i,t'}-YT_{i,t''})\right.$$
$$\left.-\sum_{j\in\{D=0\}} w(i,j)[(YC_{j,t}-YC_{j,t'})-(YC_{j,t'}-YC_{j,t''})]\right). \tag{7}$$

V. Results

The propensity score matching proved to be successful for the different definitions of the part-time job treatment variable that we studied. Our probit specification predicts the propensity to work part-time well. The goodness of fit of the probits is high: on average, they correctly predict the treatment status in approximately 75% of the cases.

In addition, our propensity scores show a large common support which is important in order for the propensity score approach to be valid (Smith and Todd, 2005). This is illustrated below in Figure 1, which reports the kernel density estimates of the propensity scores for working and non-working students, according to gender.

Table 3 presents the results for working in grade 12. Note that all of the results we comment on are conditional on not working in grade 10. Conditioning on the working status in grade 10 allows us to control for unobservable factors that could affect both the decision to work part-time in grade 10 and in grade 12 and that might yield biased CDiD as well as CDiDiD estimates. Therefore, we basically identify the effect of working part-time in grade 12 by comparing the test scores of *treated* individuals switching from non-working to working between grades 10 and 12 with the test scores of *untreated* individuals neither holding a part-time job in grade 10 nor in grade 12.[19] Simple propensity score matching differences suggest a negative effect of working in grade 12 on math scores. On the contrary, with OLS and propensity score matching estimates, the effect on reading scores are never statistically significant. However, as argued before, while controlling for selection on observables, both OLS and simple propensity score matching differences are likely to lead to biased results because of the failure to take unobserved heterogeneity into account and, as such, to prescribe spurious treatment effects to working in grade 12.

Except for females' math scores, the CDiD and CDiDiD estimators do not show any negative effect of working part-time in grade 12. The point estimates for males are even positive for math and reading, but still not significant when allowing for group-specific time trends with the CDiDiD specification.[20] Thus, once controlling for selection on observables and unobservables, we find insignificant effects of working during grade 12 on reading and math scores for males but not for females. The latter experience a negative effect of part-time work on math score, which is nevertheless fairly small and only signifi-

[19]Among the 1,817 male students (2,563 female students) not working in grade 10, 953 (1,510) hold a part-time job in grade 12 and thus are considered as being treated.

[20]The fact that some of the CDiD estimates are significantly different from the estimates obtained under the alternative CDiDiD specification suggests differential time trends in test scores according to the working status in grade 12. In the following, we focus on the more robust CDiDiD estimates of part-time work effects.

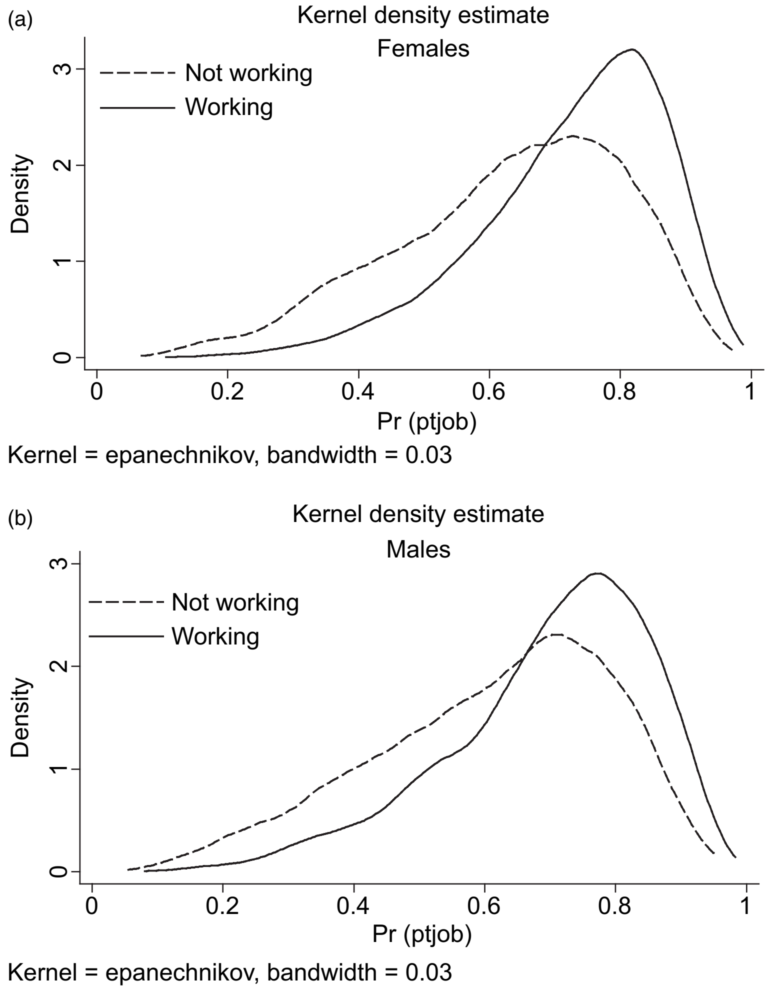

Figure 1. Common supports of the propensity scores

cant at 10%. Overall, these results therefore suggest a negligible effect of part-time work during grade 12 on academic attainment.

Turning to Table 4, where we examine different definitions of working in grade 12 (stratified by intensity and occupation), we generally find a similar story. Examining the intensity of hours, for example, prior literature generally identifies working long hours with a negative effect on test scores. A similar treatment is considered here where working 21 hours or more per week appears to have a detrimental impact on math and reading scores when using the OLS and propensity score matching estimators. However, when controlling for unobservables, we find that the point estimates become less negative, or even positive, suggesting that selection on unobservables is occurring when deciding whether to work part-time in grade 12. We find that, generally, in the CDiD estimates, males experience a small positive effect from working part-time in grade 12 (though generally insignificant) whilst women experience a small negative effect from working part-time in grade 12 (generally also insignificant). This effect is insignificant in most of the cases when the

TABLE 3

Estimation of the effect of part-time work

Part-time work effect, job definition 1. Anyone who had a part-time job in grade 12

	Females		*Males*	
	Parameter	*SE*	*Parameter*	*SE*
Math, OLS	−0.20	0.25	−0.30	0.31
Read, OLS	0.15	0.29	0.22	0.39
Math, PMatch	−0.79**	0.32	−1.08***	0.41
Read, PMatch	−0.32	0.39	0.18	0.48
Math, DiD	−0.36	0.22	0.25	0.20
Read, DiD	−0.31	0.32	0.93***	0.36
Math, DiDiD	−0.67*	0.39	0.25	0.41
Read, DiDiD	−0.42	0.60	0.85	0.52

Notes: Significant at: *10%, **5% and ***1%. Bootstrap standard errors with 200 replications. Cross-validated bandwidth for the local linear regressions. Evaluation outcomes have been expressed as parameter and standard errors. Sampling weights are used throughout.
Source: National Education Longitudinal Study of 1988.

parallel trend assumption is relaxed with the CDiDiD specification. In particular, while naïve OLS estimates yield a significantly negative effect on math scores of working part-time 21 hours or more per week (at the 1% level for females and at the 10% level for males), the estimates become insignificant when accounting for selection on unobservables with our preferred CDiDiD specification. Interestingly, this suggests that, in this context, the detrimental effect on schooling performance of working many hours per week, which is often found in the literature, is actually attributable to a selection effect.

Overall, our results therefore suggest that, as regards to academic achievement, working during high school should not see stricter regulatory rules imposed. Noteworthy, this conclusion contrasts with the work by Tyler (2003) on the same dataset, who argues that implementing more restrictive child labour laws would be beneficial to academic achievement.[21]

Note finally, relatively to the previous work of Tyler (2003), that the non-significance of most of our CDiDiD estimates is not only driven by higher standard errors. Indeed, in his article Tyler (2003) found a negative effect of around 0.20 per hour of part-time work on math and reading scores in grade 12. In comparison, our point estimates suggest a much lower hourly effect. For instance, the estimated effect of working 21 hours or more is always below 1, which is consistent with an hourly effect below 0.05. Besides, examining the only part-time work effect which is significant at 5% with our most flexible CDiDiD specification, that is the effect of working part-time in grade 12 for females not working as babysitters, lawn or household workers, the estimated negative effect of 0.66 is consistent with an hourly effect below 0.06 (as the average amount of hours worked for this category of individuals is 12.5).

[21]Although the context is different, our results also differ markedly from those obtained by Stinebrickner and Stinebrickner (2003), who conclude to a substantial academic cost to working part-time while enrolled in college.

TABLE 4

Estimation of the effect of part-time work: by number of hours worked and type of work

	Part-time work effect, job definition 2. Anyone who had a part-time job in grade 12 and worked 0–10 hours per week				*Part-time work effect, job definition 5. Anyone who had a part-time job in grade 12, but did not work as a babysitter/lawn/household worker*			
	Females		*Males*		*Females*		*Males*	
	Parameter	*SE*	*Parameter*	*SE*	*Parameter*	*SE*	*Parameter*	*SE*
Math, OLS	0.13	0.33	0.35	0.37	−0.19	0.25	−0.08	0.31
Read, OLS	0.30	0.34	0.55	0.51	0.27	0.28	−0.01	0.39
Math, PMatch	−0.35	0.50	−1.87*	1.09	−0.70*	0.37	−0.67*	0.39
Read, PMatch	0.47	0.65	0.01	0.54	−0.20	0.40	0.21	0.47
Math, DiD	−0.06	0.45	−0.05	0.51	−0.34	0.23	0.24	0.24
Read, DiD	0.18	0.50	0.98	0.85	−0.35	0.33	0.86**	0.34
Math, DiDiD	−0.10	0.56	−1.35	0.99	−0.66**	0.33	0.17	0.43
Read, DiDiD	0.43	1.05	1.15	1.40	−0.49	0.60	0.53	0.47
	Part-time work effect, job definition 3. Anyone who had a part-time job in grade 12 and worked 11–20 hours per week				*Part-time work effect, job definition 6. Anyone who had a part-time job in grade 12, but were salespersons/fast food workers/grocery clerks*			
Math, OLS	0.19	0.27	−0.01	0.38	−0.07	0.25	0.50	0.35
Read, OLS	0.19	0.32	0.59	0.50	0.04	0.31	0.42	0.48
Math, PMatch	−0.50	0.40	−0.59	0.55	−0.90**	0.37	−0.69	0.48
Read, PMatch	−0.54	0.39	0.13	0.65	−0.76*	0.40	1.00***	0.38
Math, DiD	−0.04	0.22	0.79**	0.36	−0.30	0.24	0.44	0.33
Read, DiD	−0.17	0.32	1.05**	0.49	−0.48	0.32	1.07*	0.55
Math, DiDiD	−0.54*	0.32	1.21*	0.67	−0.64	0.40	0.57	0.64
Read, DiDiD	−0.15	0.63	0.56	0.56	−0.68	0.56	0.51	0.70
	Part-time work effect, job definition 4. Anyone who had a part-time job in grade 12 and worked 21 or more hours per week				*Part-time work effect, job definition 7. Anyone who had a part-time job in grade 12, but worked weekends only*			
Math, OLS	−0.85***	0.32	−0.72*	0.40	0.17	0.42	0.24	0.44
Read, OLS	−0.40	0.39	−0.73	0.53	0.43	0.46	0.61	0.68
Math, PMatch	−0.80	0.53	−1.03	0.69	−0.73	0.69	−0.48	0.47
Read, PMatch	−0.85*	0.49	−0.04	0.80	0.10	0.98	0.35	0.59
Math, DiD	−0.50**	0.21	−0.14	0.53	−0.10	0.55	0.05	0.26
Read, DiD	−0.72**	0.32	0.74*	0.44	0.33	0.69	1.40	0.91
Math, DiDiD	−0.25	0.35	0.20	0.74	−0.06	0.49	−1.08*	0.59
Read, DiDiD	−0.36	0.63	0.75	0.80	1.25	1.37	1.65	1.39

Notes: Significant at: *10%, **5% and ***1%. Bootstrap standard errors with 200 replications. Cross-validated bandwidth for the local linear regressions. Sampling weights are used throughout.
Evaluation outcomes have been expressed as parameters and standard errors.
Source: National Education Longitudinal Study of 1988.

VI. Conclusion

In this article, we contribute to the literature regarding the effect of working while studying by employing a semiparametric propensity score matching approach combined with

DiD and DiDiD to address selection on observables as well as unobservables associated with part-time work decisions during grade 12. Unlike most of previous attempts in this literature to circumvent the endogeneity issue, our approach does not consist in finding an instrument, whose validity is often questionable, for part-time work decisions. Our identification strategy takes advantage of the longitudinal nature of the NELS:88 as well as its unusual richness in terms of variables related to part-time work decisions and educational outcomes, which is, as it is shown by Smith and Todd (2005), central for a matching-based estimator to perform well. Once selection is controlled for, we find little to no short-term effects of part-time work during grade 12 on reading and mathematics test scores.

In line with most of the recent articles estimating the impact of part-time work on educational attainment, our analysis stresses the need to control for selection on unobservables to estimate a causal effect of part-time working. For instance, while a very significant detrimental effect of part-time work during grade 12 is found on math scores for male students when controlling for differences in observable characteristic with a matching approach, no significant effect remains when we also control for differences in unobservable characteristics using CDiD and DiDiD. Furthermore, our results suggest some differences in test scores time trends according to the working status in grade 12, thus highlighting also the need to control for selection in a sufficiently flexible way.

In conclusion, we find that the causal effect on educational attainment of working during grade 12 in high school is in most cases negligibly small. Our results therefore suggest a negligible academic cost, in terms of test scores, to part-time working during grade 12. From a policy point of view, one could thus argue that more stringent child labour laws are unlikely to be conductive in achieving higher attainment scores and that, as regards to educational achievement, working during high school should be neither encouraged nor discouraged.

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Appendix

TABLE A1

Results of the propensity score probit for the job definition 1 (PTJ G12)

	Males		*Females*	
	Coefficient	*SE*	*Coefficient*	*SE*
Ethnicity				
Ref: Ethnicity white				
Asian, Pacific	−0.213	0.086	−0.268	0.083
Hispanic	−0.175	0.076	−0.214	0.072
Black	−0.414	0.084	−0.486	0.074
American Indian	−0.138	0.232	−2.740	0.006
Geographical region				
Ref: Northeast				
Midwest	0.151	0.060	0.148	0.060
South	−0.097	0.059	−0.227	0.057
Parental education expenditure				
Ref: No parental education expenditure				
Less than $500	0.171	0.070	0.011	0.066
$15,000 or more	−0.270	0.106	−0.282	0.108
Parental employment				
Father employed	0.174	0.079	0.041	0.074
Ref: Mother occupation office worker				
Tradeperson	−0.285	0.153	−0.031	0.141
Farmer	−0.437	0.295	−0.691	0.335
F-T Homemaker	−0.110	0.066	−0.163	0.064
Labourer	−0.488	0.178	−0.299	0.173
Small business owner	−0.324	0.158	−0.016	0.153
Teacher	−0.038	0.089	−0.173	0.088
Technical worker	−0.065	0.151	−0.261	0.135
Otherwise	−0.240	0.105	−0.230	0.115
Ref: Father occupation office worker				
Machine operator	−0.184	0.111	−0.213	0.111
Professional II	−0.176	0.151	−0.456	0.150
Small business owner	0.095	0.143	−0.255	0.143
Technical worker	−0.322	0.153	−0.075	0.155
Other	−0.116	0.131	−0.274	0.128
Number of siblings				
Ref: One sibling				
No Siblings	0.024	0.087	−0.207	0.090
Four	0.146	0.084	−0.011	0.082
School type				
Ref: School type public				
Catholic	0.163	0.100	0.031	0.100
Private	−0.311	0.096	−0.143	0.098

(*continued overleaf*)

TABLE A1

(*Continued*)

	Males		*Females*	
	Coefficient	*SE*	*Coefficient*	*SE*
Racial conflict at school				
Ref: School has no racial conflict problem				
Racial Conflict – serious problem	0.099	0.050	0.001	0.048
Racial Conflict – moderate problem	0.231	0.125	−0.277	0.103
School work programme				
Ref: School has school to work programme				
Workplace programme – Yes	0.050	0.049	0.160	0.047
Community work programme – missing	0.308	0.171	0.084	0.174
Proportion of pupils with English as a second language				
Ref: 0% of school speaks English as a second language				
Between 0% and 5%	0.065	0.049	0.161	0.049
Pupils' educational aspirations				
Ref: Grade 8 aspirations higher school after college				
Won't finish high school.	−0.646	0.293	−0.116	0.323
Voc training after high school	0.309	0.090	0.132	0.089
Will attend college	0.191	0.076	−0.021	0.072
Grade 8 test scores				
Grade 8 reading	0.082	0.023	0.054	0.024
Grade 8 reading-squared	−0.001	0.000	0.000	0.000
Constant	−1.515	0.687	−2.081	0.727
N	4,728		5,159	
Prob. > chi-square	0.000		0.000	
Pseudo R^2	0.066		0.084	

Notes: Only variables with significant coefficients at 10% are reported. PTJ G12, Part-time job in grade 12.

Source: National Education Longitudinal Study of 1988.