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ABSTRACT

Student Work, Educational Achievement, and Later Employment: A Dynamic Approach*

This study examines the direct and indirect impact (via educational achievement) of student work during secondary education on later employment outcomes. To this end, we jointly model student work and later schooling and employment outcomes as a chain of discrete choices. To tackle their endogeneity, we correct for these outcomes' unobserved determinants. Using unique longitudinal Belgian data, we find that pupils who work during the summer holidays of secondary education are 15.3% more likely to have a job three months after leaving school. This premium to student work experience is higher when pupils also work during the academic year and diminishes for later employment outcomes. When decomposing this total effect, it turns out that the direct returns to student work overcompensate its non-positive indirect effect via tertiary education enrolment.

JEL Classification: I21, J24, C35

Keywords: student employment, transitions in youth, education, labour, dynamic treatment

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1 Introduction

Throughout the past decades, many OECD countries have incentivised youth to combine their full-time education with student work (Adriaenssens et al., 2014; Orr et al., 2011; Scott-Clayton and Minaya, 2016). This is not surprising. From society's point of view, student employment provides a flexible source of labour. In addition, for individual students, income from student work may help satisfy their consumption aspirations (Baert et al., 2016b). However, to judge (and refine) the general incentives for combining study and work, one should also consider the long-term perspective. In this respect, studies show that students' work decisions may affect their educational achievement and later labour market outcomes (Hotz et al., 2002; Neyt et al., 2017; Ruhm, 1997). In the present study, we attempt to gain a deeper understanding of whether student employment during secondary education affects later labour market outcomes. We focus both on their direct relationship, keeping educational achievement constant, and on their indirect relationship via educational achievement.

In the past decades, scholars have referred to general (economic) theoretical frameworks to understand how student work may affect later labour market success (Baert et al., 2016b; Geel and Backes-Gellner, 2012; Molitor and Leigh, 2005). First, according to standard Human Capital Theory (Becker, 1964) employment experience during academic studies may directly provide students with hard, marketable skills and knowledge as well as general (soft) skills, such as good work habits, maturity, responsibility, and learning to deal with authority. These skills and knowledge may lead to additional returns in the labour market. Moreover, as student jobs might complement (and *ipso facto* foster) in-class education and alleviate financial constraints on future education, an additional indirect positive effect on pupils' human capital may be expected. However, following the same theory, the time-use trade-off between working and studying may also bring about a negative indirect impact of student employment. Indeed, maintaining substantial employment schedules during the academic year may interfere with learning and academic performance. Second, following Signalling Theory (Spence, 1973), employers might use student employment to sort job seekers according to abilities that are unobserved by these employers. In particular, work experience during the academic year might be a strong signal, as only highly capable students can manage to combine study and work successfully. Thus, student employment may positively affect hiring chances even without augmenting human capital. Finally, according to Social Network Theory (Granovetter, 1973) student work experience might increase social capital, which can be used in the labour market. Indeed, student workers may collect valuable market information and establish personal relationships that will help them find a better job later.

Recent peer-reviewed research examining the aforementioned theoretical expectations with empirical reality is scarce. More specifically, we are aware of eight studies published in a journal ranked in the field of economics in Web of Science since Ruhm's (1997) seminal work. Table 1 summarises their results.[1] While all European studies investigated the effect of student work during tertiary education, most North American studies focused on the premium of student employment during secondary education. First, the studies based on European data have found positive effects of student work on later economic attainment, albeit only for particular groups of student workers (individuals with a student job related to their field of study in Geel and Backes-Gellner (2002)) or for particular outcomes (only a short-run positive effect in Häkkinen (2006)). Second, research on data on the United States has yielded positive as well as zero and negative effects. Light (1999; 2001) and Molitor and Leigh (2005) found a positive relation between the total hours of student employment and later wages. Ruhm (1997) identified comparable correlations but instrumental variables estimates led to zero effects and Hotz et al. (2002) found a zero effect of student work in secondary education and a negative effect (except for African Americans) of student work in tertiary education. Third, Parent (2006) reported an overall zero effect in Canada.

TABLE 1 ABOUT HERE.

We observe two major gaps in this literature. First, as will be reviewed in the next section, previous studies may not meet the assumptions under which their empirical strategies yield results that can be given a causal interpretation. A second major gap is that most studies have identified the impact of student work conditional on students' education level at the moment of leaving school, usually by including the education level as a (set of) explanatory

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[1] Because they only focus on a very specific labour market outcome, i.e. job interview invitations, Baert et al. (2016b) are not included in this table. Scott-Clayton and Minaya (2016) are not included too because they focus on the effect of the subsidised Federal Work-Study program on individual outcomes rather than on the effect of student work *per se*. In addition, we are aware of some recent discussion papers by economists, to which we also refer in Section 2 (Alam et al., 2013; Peng and Yang, 2008). Finally, the association between student work and later employment outcomes has also been studied in other fields, like labour sociology (Marsh and Kleitman, 2005; Passaretta and Triventi, 2015).

variable(s)—assumed to be exogenous—in their regression model. As a consequence, the results they report are net of the aforementioned indirect effect student work may have through its effect on education. The other studies, which did not include these controls and thereby estimated an unconditional effect, in turn, did not decompose this total effect into a direct effect conditional on education level and an indirect effect through education level. In other words, we are not aware of any study measuring both the direct and indirect impacts (via educational achievement) of student work during secondary education on later employment outcomes.

In the present study, we jointly model student work during secondary education and later schooling and employment outcomes as a dynamic discrete choice model. This approach allows us to solve the endogeneity of these variables by controlling for a random effect affecting the subsequent outcomes (Heckman and Navarro, 2007; Hotz et al., 2002). Based on the model parameters, the impact of multiple forms of student work on multiple later outcomes is simulated in terms of Average Treatment effects on the Treated (ATTs). This is done by contrasting the outcomes of those with a particular student employment experience to those that would have been obtained in the counterfactual of no student employment experience. The dynamic nature of our model enables us to contrast the total ATTs (combining direct and indirect effects) to direct ATTs, i.e. treatment effects conditional on former schooling and labour market outcomes.

2 Endogeneity Problem

For many of the studies outlined in Table 1, it is doubtful whether their results can be given a causal interpretation due to an endogeneity problem. In general, naively estimated effects may reflect variation in factors which are unobservable to the researcher (e.g. ability and motivation) but may influence both the likelihood of student work experience and the probability of later labour market success (Hotz et al., 2002; Ruhm, 1997). As Ruhm (1997) noted, a first generation of studies treated student employment as exogenous. They examined correlations and conducted OLS regressions (controlling for a small set of observable factors besides student work). Some of the contributions listed in Table 1 are, from a methodological point of view, close to these first-generation studies—and hence methodologically unconvincing—as their primary strategy is to absorb additional sources of observable heterogeneity influencing both student work and later work outcomes. For example, Geel and Backes-Gellner (2012) use pupils' grades in secondary education and their interest in new challenges as proxies for ability and motivation. Molitor and Leigh (2005) include test scores for school and work ability based on ten questions from the Armed Forces Vocational Aptitude Battery in their linear regressions.

Four of the contributions listed in Table 1 employ instrumental variable estimation techniques and related selection models with an exclusion restriction to control for the endogeneity problem mentioned above. All these studies exploit the variation in local labour market conditions (mostly the unemployment rate) in the period of potential student work to identify the causal effect of the student work variables (in column (4) of Table 1) on later labour market outcomes (in column (3) of Table 1).[2] A key identifying assumption for this approach is that local labour market conditions during education affect later work outcomes only through student employment experience (after controlling for the local labour market conditions at the time of these later work outcomes). This is a strong assumption. Students may start their job search during their last school year(s). As a consequence, labour market conditions during their education may affect their transition to work success directly or at least indirectly via their drop-out decisions and, hence, via their human capital accumulation (Rees and Mocan, 1997). Moreover, even when an instrument is truly exogenous, imprecisely estimated effects might emerge if the instrument does not explain enough variation in the endogenous variable, as in Ruhm (1997) and Alam et al. (2013).[3]

The most ambitious—and in our opinion most convincing—approach to control for the endogeneity of student work with respect to later labour market outcomes is found in Holtz et al. (2002). Their semi-structural approach models the relevant subsequent school and work outcomes and decisions as discrete choices from age 13 onwards. Through a factor-analytic random-effects specification, individual unobserved heterogeneity is controlled for. No exclusion restriction is needed within this dynamic discrete choice model. Identification in

[2] In their recent discussion paper, Alam et al. (2013) use variation in the allocation of public summer jobs as an instrument.

[3] Instrumental variable estimation techniques only isolate a local average treatment effect (LATE), i.e. they only capture the effect of student work for pupils who are affected by the chosen instrument (Angrist et al., 2000).

Hotz et al. (2002) is achieved from the assumption that unobservable determinants of labour market outcomes are, after controlling for a set of background characteristics, orthogonal to accumulated schooling at age 13. We build on Hotz et al.'s (2002) model and relax the latter assumption in the present study.

3 Data

The statistical model outlined in Section 4 is estimated using the SONAR data. These data were created to study the transition from education to the labour market in Flanders, the northern, Dutch-speaking part of Belgium. In this section, we discuss some crucial characteristics of the Flemish education system. Then, we describe our research sample. Finally, the endogenous and exogenous variables adopted in our econometric approach are discussed.

3.1 Institutional Setting[4]

Education is compulsory in Flanders from 1 September of the year in which a child reaches age 6 until her/his 18th birthday or 30 June of the year she/he reaches age 18. Even though a regular student graduates from secondary school at age 18, this is not the case for a large number (i.e. about 40%) of Flemish pupils, since those who do not attain a certain competency level at the end of a school year are required to repeat it.

A child usually starts primary education at age 6, but entry can be delayed. Primary education comprises six consecutive years of study. After graduating from primary school, students enter secondary education. Without grade retention at primary school, pupils start secondary education the year they reach age 12. Students with a secondary school diploma can enrol directly, without an entry exam,[5] in tertiary education, i.e. college or university.

From age 15, students may combine full-time education with employment under a

[4] For more details on the educational system in Flanders, we refer to Baert and Cockx (2013), Baert et al. (2013), and De Ro (2008).

[5] The only exception is the entry exam for students who want to study medicine.

student employment contract.[6] Student employment is exempted from taxes and most social security contributions as long as the total number of working days is below a certain threshold. In our observation period, this threshold was 50 days. Student employment is subject to the Belgian minimum wage.

3.2 Sample

The SONAR data contain exceptionally rich information about both education and first labour market outcomes. The data include three representative cohorts of 3000 individuals each, born in 1976, 1978, and 1980, interviewed at age 23, with a follow up at age 26 and/or 29. In the context of the present study, we use the observations from the 1978 and 1980 cohorts as they contain uniform information on the individuals' labour supply during secondary education.

From the original sample of 6000 individuals, we removed pupils entering part-time education (523 individuals) because, as mentioned, they were forced to combine education with some labour market experience.[7] In addition, to have a sample of pupils with a homogeneous educational background, we removed from the sample (i) individuals who permanently or temporarily needed special help[8] and were therefore in special schools (99 individuals) and (ii) individuals who had already experienced more than one year of grade retention by age 15 (76 individuals). Finally, we excluded 30 individuals with inconsistent observations and 207 individuals with missing information for at least one explanatory variable used in the econometric model outlined below.

3.3 Endogenous Variables

At age 23, participants in the SONAR survey were asked whether they had been employed as

[6] From that age on they may also leave full-time education to combine a part-time education programme with an apprenticeship or a regular (part-time) job. In fact, part-time education and student employment are conditional on not having more than one year of grade retention when turning age 15. However, pupils with more than one year of retention are removed from our data (see below), so this condition is not binding within our sample.

[7] Analyses in which these individuals were retained yielded the same conclusions as those mentioned in Section 5. The results of the additional analyses are available on request.

[8] Due to physical and/or mental disability, serious behavioural and/or emotional problems, or serious learning difficulties.

a student worker during secondary education and, if so, whether this student work was done during the summer or during the academic year. Only 139 individuals said they were only a student worker during the academic year. As a consequence, modelling this particular outcome of student work experience was unfeasible. Therefore, we dropped these individuals from our sample.[9] After applying this final selection criterion, we ended up with a sample of 4926 pupils who were observed for each transition modelled in our econometric approach.

Panel A of Table 2 displays summary statistics of the schooling and labour market outcomes modelled in our econometric model: (any) delay at age 15,[10] student work experience, secondary education graduation, tertiary education enrolment, employed three months after leaving school, employed one year after leaving school, and employed five years after leaving school. These summary statistics are presented at the level of the total sample and three subsamples by student employment experience. The data reveal that 1406 individuals (28.5%) never worked during secondary education, 2941 (59.7%) worked only during the summer, and 579 (11.8%) worked during both the summer and the academic year. Clearly, the latter category of individuals enrols with a lower probability into tertiary education when compared with the other two categories. In addition, in line with the non-negative relationship between student work experience and later employment found in most previous studies (see Section 1), in our data the individuals with student work experience are more often employed than those without student work experience, both in the short- and long-term. However, this correlation might not be interpreted as a causal relation because it might also (partly) be driven by selection on educational attainment or other observable or unobservable heterogeneity, for which we control in our econometric strategy.

3.4 Exogenous Variables

In this subsection, we describe the explanatory variables used in our econometric strategy. The choice of covariates is restricted by their availability, their required (strict) exogeneity,

[9] As a—favourable—consequence of this choice, we were able to model student work during secondary education by means of an ordered logit specification (see below). As a robustness check, we included these students in the option of working during the summer and the academic year. This hardly changed the estimation and simulation results.

[10] In fact, this outcome is measured by observing the grade in which pupils start in September of the year in which they turn 14 years old. If they are 'on time', they should be in the third grade of secondary education by then.

and their relevance based on the existing research.

We include the following social background characteristics of the 4926 pupils as explanatory variables: gender, migration background (measured as a dummy capturing a foreign nationality of the maternal grandmother), the educational attainment of the mother and the father (measured as the number of years of successful schooling beyond primary education), number of siblings, and day of birth. The first five variables are standard and have also been included by other researchers (Belzil and Poinas, 2010; Cameron and Heckman, 2001). The day of birth is included to control for relative age within the birth cohort, which is found to positively affect cognitive and non-cognitive achievements in both the short- and long-term (Angrist and Krueger, 1991; Baert et al., 2013; Bedard and Dhuey, 2006; Fumarco and Baert, 2017).

Panel B of Table 2 reports descriptive statistics of these variables by student work experience. It shows that females are somewhat underrepresented in the sample of individuals with a student job only during the summer, but overrepresented in the sample of students who worked both during the summer and the academic year. Student workers have fewer siblings than individuals with no student work experience.

TABLE 2 ABOUT HERE.

Besides controlling for these personal characteristics, for each outcome modelled in our econometric strategy we include the unemployment rate at the district level at the moment of this outcome as a time-varying indicator of the labour market conditions (capturing also, to some extent, the economic differences by region). More concretely, we control for this unemployment rate in 1994, i.e. the earliest year in which it was registered, for the delay at age 15 outcome. For the student work and secondary education graduation outcomes, we control for this unemployment rate the year in which the pupils turned age 16 and age 18, respectively. For the tertiary education enrolment and employment outcomes, we control for this unemployment rate in the year and month, respectively, in which this outcome is realised.

4 Methods

In this section, we present our econometric approach. As mentioned before, this approach has two aims. First, it explicitly controls for determinants of student work decisions, educational achievement, and employment outcomes that are unobservable in our data (and, *ipso facto*, for the endogeneity problem outlined in Section 2). Second, it allows us to decompose the total effect of student work on employment outcomes in a direct effect (conditional on educational achievement and earlier employment outcomes) and an indirect effect via educational achievement and earlier employment outcomes.

4.1 Econometric Specification

Our model is a dynamic discrete choice model. Cameron and Heckman (1998; 2001) introduced this type of model to control for the dynamic selection in educational outcomes. This approach has been applied and refined by, among others, Baert and Cockx (2013), Baert et al. (2015), Baert et al. (2016a), Belzil and Poinas (2010), Colding (2009), and Colding et al. (2009). As previously mentioned, Hotz et al. (2002) used this framework to tackle the endogeneity of student work and later employment outcomes. We improve their strategy by minimising our model's initial conditions problem. In addition, we propose a simulation strategy (in Section 4.3) that allows us to distinguish between the direct effect of student work on later employment outcomes—as measured in Hotz et al. (2002)—and its indirect effect via educational attainment.

In line with the literature, our model is specified as a sequence of ordered logistic probabilities that are partially determined by unobserved heterogeneity. More specifically, we model seven outcomes: (i) educational delay at age 15, (ii) student work during secondary education, (iii) secondary education graduation, (iv) tertiary education enrolment, (v) employment three months after leaving school, (vi) employment one year after leaving school, and (vii) employment five years after leaving school. Outcome (i) captures the educational status at the moment one decides to supply labour as a student worker (and may affect all later outcomes), labelled in the literature as the initial conditions.

The choice set for a specific outcome, denoted by C^O, is a set of ordinal numbers:

$C^O = \{0,1,\ldots,n^O\}$, where n^O defines the number of ordered choices that can be made for outcome O minus 1. With respect to outcome (ii), three outcome values are possible ($n^O = 2$): no student work experience (outcome value 0), student work only during the summer (outcome value 1), and student work during both the summer and the academic year (outcome value 2).[11] All other outcomes are binary in nature ($n^O = 1$).

The optimal choice $\hat{c}_i^O$ of an individual i with respect to outcome O is the following:

$$\hat{c}_i^O = c \in C^O \quad if \quad \omega_c^O < U_{i,c}^O \leq \omega_{c+1}^O, \tag{1}$$

where $U_{i,c}^O$ is the latent utility of choice c for outcome O, and ω_c^O and ω_{c+1}^O are threshold utilities ('cut-off values') that determine the ordered choice ($\omega_0^O \equiv -\infty$ and $\omega_{n^O+1}^O \equiv +\infty$). In line with the literature, we approximate this $U_{i,c}^O$ by a linear index:

$$U_{i,c}^O = Z_i \alpha^O + R_i^O \beta^O + V_i^O \gamma^O + \nu_{i,c}^O. \tag{2}$$

In this equation, Z_i is a vector representing the exogenous variables as observed for individual i, and R_i^O captures the unemployment rate at the district level at the moment of outcome O, both of which are described in Section 3.4. V_i^O is the vector of endogenous outcomes that are realised before outcome O. α^O , β^O , and γ^O are the vectors of associated parameters and $\nu_{i,c}^O$ is unobservable from the researcher's point of view.

Specifically, we assume that $\nu_{i,c}^O$ is characterised by the following factor structure:

$$\nu_{i,c}^O = \delta^O \eta + \varepsilon_{i,c}^O, \tag{3}$$

in which η is a random effect, independent of $\varepsilon_{i,c}^O$, and independent across people, which captures unobserved determinants of the outcomes in the model. The outcome-specific coefficient δ^O is normalised to 1 for the first modelled outcome. $\varepsilon_{i,c}^O$ is the i.i.d. error term, which is logistically distributed.

As a consequence, we can write the probability of a particular outcome value as:

[11] We also estimated our model with this outcome specified as multinomial logit instead of ordered logit. This did not change the research conclusions.

$$Pr(\hat{c}_i^O = c | Z_i, R_i^O, V_i^O, \eta; \vartheta) = \frac{exp(\omega_{c+1}^O - Z_i\alpha^O - R_i^O\beta^O - V_i^O\gamma^O - \delta^O\eta - \varepsilon_{i,c}^O)}{1 + exp(\omega_{c+1}^O - Z_i\alpha^O - R_i^O\beta^O - V_i^O\gamma^O - \delta^O\eta - \varepsilon_{i,c}^O)} - \frac{exp(\omega_c^O - Z_i\alpha^O - R_i^O\beta^O - V_i^O\gamma^O - \delta^O\eta - \varepsilon_{i,c}^O)}{1 + exp(\omega_c^O - Z_i\alpha^O - R_i^O\beta^O - V_i^O\gamma^O - \delta^O\eta - \varepsilon_{i,c}^O)}, \quad (4)$$

in which we denote the vector of unknown parameters by ϑ. The likelihood contribution $\ell_i(Z_i, R_i^O, V_i^O, \eta; \vartheta)$ for any sampled individual, conditional on the unobservable η, is then constructed by the product of the probabilities of the choices realised in the data for the seven modelled outcomes.

Following the literature, we adopt a non-parametric discrete distribution for the unobserved random variable η. We assume that this distribution is characterised by an a priori unknown number of *K* points of support η_k to which are assigned probabilities $p_k(q)$ specified as logistic transforms:

$$p_k(q) = \frac{exp(q_k)}{\sum_{j=1}^{K} exp(q_j)} \quad with \quad k = 1,2,..K; q \equiv [q_1, q_2, ..., q_K] \; and \; q_1 = 0. \quad (5)$$

Hence, the unconditional individual likelihood contribution for individual *i* is:

$$\ell_i(Z_i, R_i^O, V_i^O; \vartheta, q) = \sum_{k=1}^{K} p_k(q) \ell_i(Z_i, R_i^O, V_i^O, \eta_k; \vartheta). \quad (6)$$

As Cameron and Heckman (1998; 2001) and Hotz et al. (2002) show, identification of the random effect is proven if our initial condition, i.e. delay at age 15, is free of selection. This means that η should be independent of Z_i and R_i^O, which is an assumption comparable to that of Hotz et al. (2002). However, to provide a firmer basis for its identification, we impose an exclusion restriction on our model. Specifically, we include delay at the start of primary education as an explanatory variable only with respect to the initial condition. So, we assume that this variable only affects the later outcomes through delay at age 15.[12]

4.2 Model Selection

We estimated the coefficients for the model presented in the previous subsection with a

[12] Indeed, if we include the instrument in the (ordered) logit models for the later outcomes, the related coefficient is never statistically significant from 0. Moreover, including this variable for all models neither changes the coefficient estimates for the other variables nor affects the simulation results.

maximum likelihood estimation following Gaure et al. (2007). Heterogeneity types were gradually added until the log-likelihood value of the model failed to increase.

Table A–1 in the Appendix reports the number of parameters, the log-likelihood, and the Akaike Information Criterion (AIC)[13] values of the model according to the number of heterogeneity types K included. The lowest AIC is obtained for $K = 3$. The coefficient estimates for this model are displayed in Table A–2. Unless otherwise stated, the simulations below are based on these parameter estimates.

The coefficient estimates in Table A–2 provide further evidence that controlling for unobserved heterogeneity is important. First, the proportion of each of the three heterogeneity types is substantial ($p_1 = 72.4\%$, $p_2 = 22.4\%$, and $p_3 = 5.3\%$).[14] Second, almost all (other) parameters of the unobserved heterogeneity distribution (i.e. the η_k's and δ^O's) are highly significantly different from 0. Clearly, the second and—*a fortiori*—the third heterogeneity type, when compared with the first type, are more likely to graduate from secondary education and to enrol in tertiary education and less likely to be employed three months, one year, and five years after leaving school, *ceteris paribus*.

In addition, when comparing the estimation results in Table A–2 with the corresponding results for $K = 1$, which are available on request, substantial differences in some parameters stand out. Most importantly, with respect to being employed one year after leaving school, the parameter estimate of student work during the summer increases from 0.224 ($p = 0.033$) to 0.516 ($p = 0.002$) and that of student work during the summer and the academic year increases from 0.181 ($p = 0.257$) to 0.770 ($p = 0.008$) after controlling for unobserved heterogeneity. We return to the importance of controlling for unobserved heterogeneity below.

4.3 Simulation Strategy

Based on the estimated parameters for our preferred model, we simulate student work, educational achievement, and employment outcomes. To answer our research questions, we

[13] Following the argument in Gaure et al. (2007), we believe that the AIC is the preferable criterion for our sample size.

[14] For instance, following equation (5), $p_2 = exp(-1.174)/(exp(0) + exp(-1.174) + exp(-2.618))$.

run these simulations under different counterfactual scenarios with respect to the student work outcome.

For each analysis, we randomly draw 999 vectors from the asymptotic normal distribution of the model parameters. Subsequently, in each of the 999 draws, the parameters are used to calculate the probabilities associated with each heterogeneity type. These probabilities are then used to randomly assign a heterogeneity type to each pupil in the sample. Thereafter, based on these randomly drawn parameters and the assignment of individuals to a heterogeneity type, the full sequence of schooling and labour market outcomes is simulated for each pupil in the sample (for each draw).

More concretely, each outcome is simulated sequentially based on its (ordered) logit specification reported in Section 4.1. These specifications yield, for each individual in each draw, a probability for each potential outcome value. These probabilities are then translated to segments on the unit interval. To determine the particular outcome value for each individual in each draw, a number is generated from the standard uniform distribution. The outcome value assigned to the individual depends on the segment in which this random number falls. Once an outcome is assigned, it is saved and conditioned upon for the subsequent outcomes.

In the sequel, the model prediction of a particular outcome refers to the average of these 999 replications. The 95% confidence intervals are constructed by choosing the appropriate percentiles of the 999 simulated probabilities.

4.4 Goodness of Fit

In Table A–3 we compare the outcome predictions as observed in our data with the simulated predictions based on our model (and the data for the exogenous variables). Clearly, actual and simulated probabilities for the mentioned outcomes are very comparable. More concretely, the actual probabilities always fall within the 5% confidence intervals of the simulated probabilities. Therefore, we conclude that our model captures the dynamic choices in student work, educational attainment, and employment outcomes quite well.

5 Results

Table 3 presents the ATTs with respect to the two student work treatments. ATTs for a particular outcome are estimated as a model prediction (following Section 4.3) of the following quotient: the numerator is the average outcome across individuals in the sample who are in the simulation assigned to the treatment group (therefore, assigned to a particular form of student employment); the denominator is the average outcome across the same individuals when the counterfactual treatment of no student work is imposed on them.

We distinguish between ATTs capturing total effects (Section I of Table 3) and ATTs capturing direct effects (Section II of Table 3). For total effects, all schooling and labour market outcomes realised in the simulations after the student work decision are dependent on this treatment or the counterfactual situation of no treatment. As a consequence, the treatment (and its counterfactual) may not only affect a specific later simulated outcome directly (via the model's coefficients capturing this direct impact), but also indirectly (via the model's coefficients capturing the effect of former outcomes that might, in turn, be affected directly by the student work outcome).[15] Therefore, these total effects can also be labelled as 'unconditional effects', i.e. effects without keeping former schooling and labour market outcomes fixed. In contrast, for direct effects, only the (logit specification of the) outcome of interest is affected by the imposed counterfactual. All outcomes realised earlier in the model are fixed to those of the treatment group. As a result, the treatment (and its counterfactual) only affects the outcome of interest directly (via the model's coefficients capturing this direct impact). These direct effects can also be labelled 'conditional effects', i.e. effects keeping former schooling and labour market outcomes fixed. In what follows, we subsequently report the total and direct effects.

First, Section I of Table 3 shows that the total effect of student work (only during the summer or during both the summer and the academic year) on secondary education graduation is virtually zero. So, we do not find evidence that time spent working crowds out

[15] For instance, the total effect of student work during the summer on employment three months after leaving school is affected by (i) coefficient 0.380 in Panel E of Table A–2 (direct effect) as well as by (ii) the interplay between coefficient 0.309 in Panel E and coefficient 0.123 in Panel C (indirect effect via secondary education graduation) and (iii) the interplay between coefficient 0.191 in Panel E and coefficient -0.147 in Panel D (indirect effect via tertiary education enrolment).

time spent on activities that enhance academic performance. Second, in contrast, we find that pupils who worked as a student both during the summer and the academic year are 16.9%[16] less likely to enrol in tertiary education when compared with similar individuals with no student work experience. No significant effect of student work experience exclusively during the summer is found. This might be explained by the stronger ties to the labour market of the former treatment group (and, as a consequence, a relatively weaker tie towards school; Baert et al., in press; Bozick, 2007; Warren, 2002) due to their more intense immersion into the labour market.

TABLE 3 ABOUT HERE.

Third, and most importantly, we find a positive total effect of student work on later employment outcomes that decreases over time. The ATT on the first employment outcome is highly significantly positive with respect to both forms of student work. Those who only worked during the summer are 15.3% more likely to be employed three months after graduation. In line with its potentially even stronger signal of skills and motivation to employers (as mentioned in the introduction), the premium of student work during both the summer and the academic year is even higher. Pupils with this kind of experience are 24.0% more likely to be employed three months after leaving school. The corresponding ATTs on employment one year after leaving school are substantially lower (7.0% and 8.7%, respectively). Finally, the unconditional ATT on employment five years after leaving school is only statistically significant with respect to student work only during the summer (2.8% higher probability of employment than comparable individuals with no student work experience). The difference in the latter ATT by type of student work is driven by the interplay between (i) the aforementioned lower probability of tertiary education enrolment among individuals who work during both the summer and the academic year and (ii) the positive effect of tertiary education enrolment on employment five years after leaving school (as can be seen in Panel G in Table A–2).

Overall, the measured total effects of student work on educational achievement and later labour market outcomes corroborate with the literature. More concretely, the ATTs on the educational outcomes are in line with the mostly non-positive effect presented by

[16] -16.9% = 0.831 – 1.

contributions focussing on the effect of student work on educational achievement (Buscha et al.,2012; Neyt et al., 2017). Also, the positive employment effects are in line with the majority of studies listed in Table 1. Moreover, the pattern of diminishing returns over time is in line with Häkkinen (2006).

Column (2) presents the corresponding ATTs (for the total effects) based on the coefficient estimates for the model without correction for unobserved heterogeneity (*K = 1*). Overall—and in line with our discussion at the end of Section 4.2—the uncorrected predictions are somewhat underestimated (in absolute value). On the one hand, the ATT with respect to student work during both the summer and the academic year on tertiary education enrolment is 4.4 percentage points smaller when not correcting for unobserved heterogeneity. This means that our preferred model corrected for unobservables of this kind of student workers that are beneficial with respect to their tertiary education enrolment. On the other hand, the ATT on employment three months after leaving school is 0.8 (student work only during the summer) to 2.0 percentage points (student work during both the summer and the academic year) smaller and the ATT on employment one year after leaving school is 1.4 to 3.0 percentage points smaller based on the model not controlling for unobserved heterogeneity. Therefore, our preferred model corrected for unobservables of the student workers that are adverse with respect to employment outcomes. These observations may (partly) explain why our treatment effects, especially those concerning our first employment outcome, are somewhat higher in magnitude than those reported by former contributions.

Column (3) displays the direct effects, i.e. ATTs after conditioning on the values for the treatment group for the preceding outcomes of our model. This direct effect equals the total effect minus the indirect effect of student work via prior endogenous variables. Given the design of our econometric model, direct and total effects are exactly the same for the schooling outcomes (they are only affected by student work outcomes in a direct way).

With respect to employment three months after leaving school, the direct ATT of student work only during the summer (15.3%) is exactly as high at the total ATT. So, the indirect impacts via secondary education graduation and tertiary education enrolment cancel each other out.[17] The direct ATT of student work during both the summer and the academic year (25.1%) is even higher than the total ATT (24.0%). So, the positive direct effect overcompensates a negative indirect effect.[18]

In contrast, the direct ATT is (somewhat) smaller than the total ATT for the later employment outcomes. For employment one year after leaving school, the direct ATT is 1.6 (with respect to student work during both the summer and the academic year) to 2.6 (with respect to student work only during the summer) percentage points smaller than the total ATT. For employment five years after leaving school, we do not find evidence of a significant direct effect, while, as mentioned before, the total ATT with respect to student work only during the summer was significant. So, we find evidence for (small) positive indirect effects. This is not surprising because for these later employment outcomes, the indirect effect is partly determined by the positive effect of student work on the first employment outcome (which, following the coefficients in Panels F and G of Table A–2, positively affects the later employment outcomes).

Finally, again, the direct ATTs based on the model without controlling for unobserved heterogeneity, as presented in column (4), are somewhat underestimated.

6 Conclusion

The objective of this research was to gain a deeper understanding of whether student work during secondary education affects later labour market outcomes. We jointly modelled student work and later schooling and employment outcomes as a dynamic discrete choice model. This approach allowed us to solve the endogeneity of these variables by controlling

[17] According to the coefficients in Panels C and E of Table A–2, secondary education graduation is (i) insignificantly positively associated with student work only during the summer and (ii) significantly positively associated with employment three months after leaving school. In addition, following the coefficients in Panels D and E of Table A–2, tertiary education enrolment is (i) insignificantly negatively associated with student work only during the summer and (ii) insignificantly positively associated with employment three months after leaving school.

[18] This negative effect is driven by the negative association between this form of student work and the schooling outcomes (Panels C and D of Table A–2) and these schooling outcomes' positive association with employment three months after leaving school (Panel E of Table A-2).

for a random effect affecting the subsequent outcomes. Moreover, the dynamic nature of our model enabled us to contrast the total effects of student work with respect to later employment outcomes to direct effects, corrected for the indirect impact of student work on later employment via schooling and earlier employment outcomes.

We found that pupils who worked during secondary education were substantially more likely to be employed three months after leaving school than comparable students without this experience. This return to student work in terms of employment chances was higher when pupils not only worked during the summer, but also during the academic year. When decomposing this total effect, it turned out that the direct effect of student work on employment three months after leaving school overcompensated a non-positive indirect effect via tertiary education enrolment. For later employment outcomes, the causal effect of student work was lower and comprised of a direct (positive) effect and an indirect (positive) effect via the first employment outcome.

These findings clearly depart from those obtained by relying on more standard statistical methods and models. First, when only controlling for observables, the returns to student work was underestimated. Second, modelling simultaneously both educational and labour market outcomes generated a much more comprehensive and nuanced view of the overall benefits and side effects of student employment than a reduced form approach.

We are in favour of future research that complements our research on the causality ('whether') of the relationship between student work and later employment outcomes with an investigation of the underlying mechanisms ('why'). To our knowledge, no study has focused on explicitly examining the empirical salience of the three theoretical channels outlined in our introduction.[19] Although unravelling their exact relative importance seems impossible, testing particular predictions of these models should be feasible. Moreover, we would be interested in heterogeneous treatment effects ('when') by dimensions other than the moment of student work as investigated in this study. In particular, it would be interesting to know more about the heterogeneity of the effect of student work by qualitative aspects of

[19] However, Baert et al. (2016b) provided some suggestive evidence in this respect. They measured the effect of student work on résumés on employers' hiring decisions, i.e. an effect that could only be driven by employer side preferences and perceptions. As these authors did not find a significant treatment effect, their results suggest that the employee side mechanisms (human capital and social capital) are crucial.

student work experience (e.g. relation to field of study) and later labour market outcomes (e.g. job match quality).

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Table 1. Literature Review

(1) **Study**	(2) **Country of analysis**	(3) **Main outcome variable(s)**	(4) **Main explanatory variable(s)**	(5) **Main result(s)**	(6) **Methodological approach**
Geel and Backes-Gellner (2002)	Switzerland	Labour market status 1 Y and 5 Y after LS	Total months of SW in TE	Positive effect, but only for SW related to study field	Parametric control for observables
Häkkinen (2006)	Finland	Yearly earnings 1 Y, 2 Y, and 3 Y after LS	Total years of SW in TE	Positive effect, but only 1 Y after LS	IV approach
Hotz et al. (2002)	United States	Wages at ages 22 and 27	Total years of SW in SE, total years of SW in TE	Negative effect of SW in TE for Hispanics and whites	DDC modelling
Light (1999; 2001)	United States	Wages during 9 Y after LS	Total hours of SW in SE	Positive effect	IV approach
Molitor and Leigh (2005)	United States	(Bi)annual wages after LS	Total hours of SW in SE and TE	Positive effect	Parametric control for observables
Parent (2006)	Canada	Wages in 1995 (age 22–24)	Any SW in SE	No effect	Selection model with exclusion restriction
Ruhm (1997)	United States	Earnings 6–9 Y after LS	Hours of SW in years of SE	No effect or positive effect, depending on specification	Selection model with exclusion restriction and IV approach

Notes. Some abbreviations are used: SW (student work), SE (secondary education), TE (tertiary education), Y (year(s)), LS (leaving school), IV (instrumental variable), and DDC (dynamic discrete choice).

Table 2. Summary Statistics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	I. Whole sample (N = 4926)		II. Sample with no student work (N = 1406)		III. Sample with student work during summer (N = 2941)		IV. Sample with student work during summer and academic year (N = 579)	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
A. Endogenous variables								
Delay at age 15	0.153	0.360	0.134	0.340	0.149	0.356	0.223	0.416
Student work experience								
No student work	0.285	0.452	1.000	0.000	0.000	0.000	0.000	0.000
Student work during summer	0.597	0.491	0.000	0.000	1.000	0.000	0.000	0.000
Student work during summer and academic year	0.118	0.322	0.000	0.000	0.000	0.000	1.000	0.000
Secondary education graduation	0.882	0.322	0.869	0.337	0.894	0.308	0.857	0.351
Tertiary education enrolment	0.687	0.464	0.703	0.457	0.703	0.457	0.566	0.496
Employed three months after leaving school	0.615	0.487	0.542	0.498	0.638	0.481	0.666	0.472
Employed one year after leaving school	0.847	0.361	0.801	0.399	0.866	0.340	0.854	0.354
Employed five years after leaving school	0.921	0.270	0.883	0.321	0.938	0.241	0.914	0.281
B. Exogenous variables								
Female gender	0.508	0.500	0.539	0.499	0.478	0.500	0.582	0.494
Migration background	0.052	0.221	0.076	0.265	0.035	0.185	0.074	0.262
Number of siblings	1.587	1.332	1.681	1.522	1.529	1.216	1.651	1.392
Mother's education after primary education (years)	5.632	3.148	5.615	3.317	5.746	3.048	5.097	3.180
Father's education after primary education (years)	6.070	3.429	6.061	3.649	6.185	3.303	5.506	3.460
Day of birth within calendar year	180.260	103.169	183.836	102.761	179.174	103.491	177.092	102.464
Delay at start of primary education	0.015	0.122	0.015	0.121	0.015	0.121	0.016	0.124

Notes. See Section 3 for a description of the variables.

Table 3. ATTs of Student Work Experience on Schooling and Labour Market Outcomes

	(1)	(2)	(3)	(4)
	I. Total effect		II. Direct effect	
	Corrected for unobserved determinants (K = 3)	No correction for unobserved determinants (K = 1)	Corrected for unobserved determinants (K = 3)	No correction for unobserved determinants (K = 1)
A. Treatment: Student work during summer				
Secondary education graduation	1.013 [0.983,1.047]	1.020 [0.990,1.051]	-	-
Tertiary education enrolment	0.989 [0.938,1.042]	1.007 [0.954,1.059]	-	-
Employed three months after leaving school	1.153*** [1.082,1.232]	1.145*** [1.067,1.230]	1.153*** [1.073,1.234]	1.143*** [1.066,1.223]
Employed one year after leaving school	1.070*** [1.029,1.115]	1.056*** [1.017,1.097]	1.044*** [1.012,1.079]	1.026 [0.994,1.059]
Employed five years after leaving school	1.028** [1.001,1.061]	1.023 [0.994,1.053]	1.017 [0.989,1.048]	1.014 [0.988,1.041]
B. Treatment: Student work during summer and academic year				
Secondary education graduation	0.996 [0.937,1.057]	1.008 [0.952,1.066]	-	-
Tertiary education enrolment	0.831*** [0.714,0.929]	0.875** [0.780,0.970]	-	-
Employed three months after leaving school	1.240*** [1.114,1.389]	1.220*** [1.083,1.369]	1.251*** [1.108,1.406]	1.209*** [1.081,1.358]
Employed one year after leaving school	1.087*** [1.015,1.167]	1.057* [0.989,1.127]	1.071** [1.006,1.139]	1.022 [0.966,1.080]
Employed five years after leaving school	1.019 [0.969,1.071]	1.009 [0.963,1.059]	1.013 [0.961,1.062]	1.004 [0.958,1.049]

Notes. The presented statistics are simulated Average Treatment effects on the Treated (ATTs) and 95% confidence intervals are given between brackets. The direct effects are not presented with respect to the schooling outcomes as these direct effects equal the total effects (no conditioning on prior endogenous variables). * (**) ((***)) indicates significance at the 10% (5%) ((1%)) significance level.

Table A–1. Model Selection

(1)	(2)	(3)	(4)
# heterogeneity types (K)	# parameters	Log-likelihood	Akaike Information Criterion
1	83	-14847.803	29861.606
2	91	-14820.527	29823.054
3	93	-14817.501	29821.001
4	95	-14817.018	29824.036
5	97	-14817.018	29828.036

Table A–2. Full Estimation Results

A. Outcome: Delay at age 15	
Female gender	-0.454*** (0.084)
Migration background	0.178 (0.174)
Number of siblings	0.125*** (0.029)
Mother's education after primary education (years)	-0.107*** (0.017)
Father's education after primary education (years)	-0.056*** (0.015)
Day of birth within calendar year	0.002*** (0.000)
Unemployment rate	0.006 (0.013)
Delay at start of primary education	2.631*** (0.269)
Cut-off value 1	1.263*** (0.236)
B. Outcome: Student work experience	
Female gender	-0.005 (0.057)
Migration background	-0.431*** (0.143)
Number of siblings	-0.034 (0.023)
Mother's education after primary education (years)	-0.010 (0.012)
Father's education after primary education (years)	-0.010 (0.011)
Day of birth within calendar year	-0.001** (0.000)
Unemployment rate	-0.006 (0.010)
Delay at age 15	0.377*** (0.084)
Cut-off value 1	-1.187*** (0.170)
Cut-off value 2	1.772*** (0.175)
C. Outcome: Secondary education graduation	
Female gender	0.503*** (0.104)
Migration background	-0.396* (0.206)
Number of siblings	-0.083** (0.037)
Mother's education after primary education (years)	0.127*** (0.020)
Father's education after primary education (years)	0.140*** (0.019)
Day of birth within calendar year	0.001** (0.001)
Unemployment rate	-0.002 (0.021)
Delay at age 15	-1.190*** (0.117)
No student work (reference)	
Student work during summer	0.123 (0.119)
Student work during summer and academic year	-0.035 (0.178)
Cut-off value 1	-0.324 (0.356)
D. Outcome: Tertiary education enrolment	
Female gender	0.697*** (0.123)
Migration background	0.217 (0.314)
Number of siblings	-0.099** (0.046)
Mother's education after primary education (years)	0.197*** (0.026)
Father's education after primary education (years)	0.204*** (0.025)
Day of birth within calendar year	0.001 (0.001)
Unemployment rate	0.123*** (0.019)
Delay at age 15	-1.131*** (0.146)
No student work (reference)	
Student work during summer	-0.147 (0.126)

Student work during summer and academic year	-1.030*** (0.231)
Cut-off value 1	2.674*** (0.483)
E. Outcome: Employed three months after leaving school	
Female gender	-0.226*** (0.066)
Migration background	-0.879*** (0.154)
Number of siblings	-0.047* (0.025)
Mother’s education after primary education (years)	-0.026* (0.013)
Father’s education after primary education (years)	-0.046*** (0.012)
Day of birth within calendar year	0.000 (0.000)
Unemployment rate	-0.101*** (0.015)
Delay at age 15	-0.157* (0.092)
No student work (reference)	
Student work during summer	0.380*** (0.075)
Student work during summer and academic year	0.623*** (0.120)
Secondary education graduation	0.309*** (0.112)
Tertiary education enrolment	0.191 (0.129)
Cut-off value 1	-1.549*** (0.210)
F. Outcome: Employed one year after leaving school	
Female gender	-0.669*** (0.137)
Migration background	-0.614** (0.257)
Number of siblings	-0.065 (0.045)
Mother’s education after primary education (years)	-0.059** (0.026)
Father’s education after primary education (years)	-0.062** (0.024)
Day of birth within calendar year	-0.001* (0.001)
Unemployment rate	-0.180*** (0.031)
Delay at age 15	-0.237 (0.162)
No student work (reference)	
Student work during summer	0.516*** (0.171)
Student work during summer and academic year	0.770*** (0.289)
Secondary education graduation	0.454** (0.176)
Tertiary education enrolment	3.259*** (0.355)
Employed three months after leaving school	2.561*** (0.206)
Cut-off value 1	-2.404*** (0.428)
G. Outcome: Employed five years after leaving school	
Female gender	-0.672*** (0.177)
Migration background	-0.466* (0.283)
Number of siblings	-0.201*** (0.050)
Mother’s education after primary education (years)	0.019 (0.034)
Father’s education after primary education (years)	-0.046 (0.032)
Day of birth within calendar year	0.000 (0.001)
Unemployment rate	-0.049 (0.043)
Delay at age 15	-0.115 (0.203)
No student work (reference)	
Student work during summer	0.290 (0.190)
Student work during summer and academic year	0.196 (0.276)
Secondary education graduation	0.832*** (0.211)

Tertiary education enrolment	1.180** (0.496)
Employed three months after leaving school	0.131 (0.200)
Employed one year after leaving school	1.227*** (0.274)
Cut-off value 1	-1.784*** (0.436)
H. Unobserved heterogeneity distribution	
q_2	-1.174*** (0.329)
q_3	-2.618*** (0.444)
η_2	-0.456*** (0.068)
η_3	-0.985*** (0.188)
δ: student work experience	0.383 (0.331)
δ: secondary education graduation	-5.532*** (0.113)
δ: tertiary education enrolment	-8.111*** (0.000)
δ: employed three months after leaving school	1.378*** (0.410)
δ: employed one year after leaving school	6.578*** (1.042)
δ: employed five years after leaving school	1.446** (0.737)
Parameters	93
Log-likelihood	-14817.501
Akaike Information Criterion	29821.001
N	4926

Notes. The presented statistics are estimated coefficients and standard errors between parentheses. * (**) ((***)) indicates significance at the 10% (5%) ((1%)) significance level.

Table A–3. Goodness of Fit

	(1) Actual probability	(2) Simulated probability [95% CI]
Delay at age 15	0.153	0.154 [0.141, 0.168]
No student work (reference)		
Student work during summer	0.597	0.595 [0.575, 0.615]
Student work during summer and academic year	0.118	0.118 [0.103, 0.131]
Secondary education graduation	0.882	0.872 [0.790, 0.893]
Tertiary education enrolment	0.687	0.656 [0.538, 0.693]
Employed three months after leaving school	0.615	0.625 [0.601, 0.657]
Employed one year after leaving school	0.847	0.858 [0.812, 0.909]
Employed five years after leaving school	0.921	0.929 [0.903, 0.945]