STUDENT WORK DURING SECONDARY EDUCATION, EDUCATIONAL ACHIEVEMENT, AND LATER EMPLOYMENT: A DYNAMIC APPROACH

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Abstract

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 discrete choices, while correcting for these outcomes' unobserved determinants. Using unique longitudinal Belgian data, we find that pupils who work during the summer holidays are more likely to be employed three months after leaving school. This premium to student work in secondary education is higher when pupils also work during the school year. Decomposing this total effect shows that the direct return to student work during secondary education overcompensates its non-positive indirect effect via educational achievement. This effect is also found to decline over time, with the premium to a combination of work during the summer and the school year becoming statistically insignificant five years after graduation.

Keywords: student employment; in-school employment; transitions in youth; education; labour; dynamic treatment

JEL-codes: I21, J24, C35.

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1. Introduction

Throughout the past decades, many OECD countries have incentivised youths to combine their full-time education with student work (Orr et al. 2011; Adriaenssens et al. 2014; 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., 2016). 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 (Neyt et al. 2018) and later labour market outcomes (Ruhm 1997; Light 2001). Based on Belgian data that track young people over time, we attempt to gain a deeper understanding of whether student employment during secondary education affects later employment chances. 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 (Molitor and Leigh 2005; Geel and Backes-Gellner 2012; Baert et al. 2016). First, according to standard human capital theory (Becker 1964) employment experience during education 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 these 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 school year may interfere with learning and academic performance.[5] Finally, if working while studying enhances students' ties to the labour market (and, as a consequence, weakens students' ties towards education; Warren, 2002; Bozick, 2007; Baert et al., 2018), their human capital may also be negatively affected through a lower participation rate in further education. 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 school year might be a strong signal, as only highly capable pupils

[5] For instance, Kalenkoski and Pabilonia (2012) show that employment during the school year decreases the time that secondary school students spend on homework.

can manage to combine study and work successfully. Thus, student employment may positively affect hiring chances even without augmenting human capital. Thirdly, according to social network theory (Granovetter 1973) high school student work experience might increase social capital, which can be used in the labour market. Indeed, student and workers may collect valuable market information and establish personal relationships that will help them find a better job later.

Recent research examining the causal impact of student work during secondary education on labour market outcomes is scarce.[6] More specifically, we are aware of seven studies published in a journal ranked in the field of economics in Web of Science since Ruhm's (1997) seminal work that examines the relationship between student work during secondary education and labour market outcomes. Table 1 summarises their results.[7] 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, although instrumental variable estimates led to zero effects. Similarly, Hotz et al. (2002), Parent (2006) and Ashworth et al. (2021) found no or even negative effects of student work during secondary education on wages when endogeneity was accounted for.

<Table 1 here>

In the present study, we address three major gaps in this literature. First, as will be reviewed in the next section, several of the previous studies on the effect of student employment during secondary education on future labour market outcomes 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 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

[6] Most previous studies examining the causal impact of working while studying have examined its impact on educational outcomes (Eckstein and Wolpin 1993; Stinebrickner & Stinebrickner 2003) or focussed on the effect of student work during tertiary education (Geel and Backes-Gellner 2002; Stinebrickner and Stinebrickner 2003; Häkkinen 2006; Joensen 2009; Passaretta and Triventi 2015). However, as the effect of working while studying on educational outcomes differs from its effect on labour market outcomes and as the effect of student work during tertiary education differs from the effect of student work during secondary education (Neyt et al. 2018), these studies are unable to answer the research questions we pose in this study.

[7] Because they only focus on a very specific labour market outcome, i.e. job interview invitations, Baert et al. (2016) 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 programme 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 (Peng and Yang 2008; Alam et al. 2013). Finally, the association between working while studying and later employment outcomes has also been studied in other fields, like sociology (Carr et al.; Brody 1996; Marsh and Kleitman 2005).

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. Third, most studies have considered wages and earnings as main labour market outcome variables rather than employment chances. We consider a focus on employment chances to be particularly relevant in a context of a labour market that is characterised by relatively high minimum wages and a strong focus on collective wage bargaining, as is the case in Belgium.[8]

To address these gaps, 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 an unobserved component that is identified by exploiting the panel structure of the data (Hotz et al. 2002; Heckman and Navarro 2007; Ashworth et al. 2021). Based on the model parameters, we are able to simulate the impact of multiple forms of student work on multiple later outcomes in terms of Average Treatment effects on the Treated (ATTs). This focus on ATTs is a clear advantage to more quasi-experimental designs, which identify a Local Average Treatment effect only. This identification of the ATTs 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 also 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

It is doubtful whether all of the results in the studies reported in Table 1 can be given a causal interpretation. 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 (Ruhm 1997; Hotz et al. 2002). 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

[8] This importance of focusing on employment chances is, among others, witnessed by the substantial gap in employment rates between high and low skilled. For instance, in 2019 in Belgium, these rates were 83.8% and 46.3% respectively (Eurostat 2020).

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, 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.[9]

Three 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 during secondary education to identify the causal effect of the student work in this period (in column (4) of Table 3.1) on later labour market outcomes (in column (3) of Table 3.1).[10] 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. Pupils may start their job search during their last school year(s) already. 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).[11]

The most ambitious – and in our opinion most convincing – approach to control for the endogeneity of student work in secondary education with respect to later labour market outcomes is found in Hotz et al. (2002) and Ashworth et al. (2021). Their semi-structural approach models the relevant subsequent school and work outcomes and decisions as discrete choices. Through a factor-analytic random effect that are identified based on the panel structure of the data, individual unobserved heterogeneity is controlled for. Both studies found the estimated wage returns to student employment in secondary education to become non-significant or even negative based on this methodology. In our analysis, we adopt a similar approach.

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[9] Similarly, for studies outside the field of economics, Carr, Wright, and Brody (1996) and Marsh and Kleitman (2005) solely control for observable differences between working and non-working students, such as students' background characteristics, earlier educational performance, and educational aspirations.

[10] Alam et al. (2013) use variation in the allocation of public summer jobs as an instrument.

[11] 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).

3. Institutional setting

3.1. Flemish education system

In this study we examine schooling and early labour market careers of Flemish youths. A schematic overview of the education system in Flanders can be found in Figure 3.1. In Flanders, there is compulsory education from September 1st of the year in which a child reaches age 6. However, before the start of compulsory education almost all children (98.6% in the school year 2016–2017) already attend pre-school education from age 2.5 on. Compulsory education ends on June 30th of the year in which a child reaches age 18 or their 18th birthday, whichever comes first. Compulsory education in Flanders is split up in two periods: primary education and secondary education. After that, individuals who want to pursue further education can enrol in tertiary education.

So, after voluntarily attending pre-school education, a child goes through six years of primary education, which she/he usually starts at age 6. However, entry can be delayed if the child does not meet pre-defined standards to be allowed to start primary education. Similarly, succession to higher years in primary education can be delayed if a child does not meet pre-defined standards at the end of a certain school year. The child is then required to repeat that school year. There is no tracking in primary education.

Then, after successfully completing primary education youths enrol in secondary education. Secondary education consists of six or seven school years (*infra*), which a student starts at age 12 if she/he was not delayed before or during primary education. Again, also during secondary education students can be delayed if they do not meet pre-defined standards at the end of a certain school year. The student is then required to repeat that school year. Secondary education is characterised by tracking. In the first two years of secondary education there are two tracks: the general track and the vocational track. From the third year on, there are four tracks, summed up from ‘highest’ to ‘lowest’ these are the general track; the technical track and the arts track (on the same ‘level’); and the vocational track. Pupils in the general track, the technical track, and the arts track go through six years of secondary education, while this extends to seven years for pupils in the vocational track. At the end of each school year, pupils can downgrade from one track to a lower track. Although in theory pupils are also allowed to upgrade (going from one track to a higher track), this does not happen in practice. From age 15 onwards, pupils can decide to enrol in part-time vocational education. In these programmes, pupils go to school for one or two days a week, while for the remaining days they are employed as an apprentice with an employer.

A final period in Flemish youths' schooling careers is – voluntary – tertiary education. Those who successfully completed full-time school-based secondary education – i.e. they did not only complete part-time vocational education mentioned in the previous paragraph – are unconditionally allowed to start any type of higher education. The only exception is for those who want to study medicine and dentistry, who have to successfully complete an entry exam. Tertiary education usually comprises three years (for Bachelor degrees) or four to five years (for most Master degrees) of schooling. However, some Master degrees are longer, such as for students who want to study medicine: they study for seven years.

3.2. Student work during secondary education

From age 15 on, pupils may combine full-time education with employment under a so-called student employment contract. 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.

4. Data

4.1. Sample

The statistical model outlined in Section 5 is estimated using the SONAR data. These data were created to study the transition from school to the labour market in Flanders, i.e. the northern, Dutch-speaking part of Belgium. The data contain rich information on both schooling and first labour market outcomes for three representative cohorts of 3,000 individuals each, born in 1976, 1978, and 1980. These individuals were 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 6,000 individuals, we removed pupils entering part-time education (523 individuals) because, as mentioned, they were forced to combine education with some labour market experience.[12] In addition, to have a sample of pupils with a homogeneous educational background, we

[12] Analyses in which these individuals were retained yielded the same conclusions as those mentioned in Section 5.5. The results of the additional analyses are available on request.

removed from the sample (i) individuals who permanently or temporarily needed special help[13] 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.

4.2. Endogenous variables

At age 23, participants in the SONAR survey were asked whether they had been employed based on a student employment contract during secondary education and, if so, whether this student work was done during the summer or during the school year. 139 individuals said they were a student worker only during the school year. As a consequence, modelling this particular outcome of work experience was unfeasible. Therefore, we dropped these individuals from our sample.[14] After applying this final selection criterion, we ended up with a sample of 4,926 pupils who were observed for each transition modelled in our econometric approach.

Panel A of Table 3.2 displays summary statistics of the schooling and labour market outcomes modelled in our econometric model: (any) delay at age 15, student work experience during secondary education, 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 1,406 individuals (28.5%) never worked during secondary education, 2,941 (59.7%) worked only during the summer, and 579 (11.8%) worked during both the summer and the school 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 in secondary education and later employment found in most previous studies (see Section 3.1), in our data the individuals with student work experience in secondary education 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.

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

[14] 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 pupils in the option of working during the summer and the school year. This hardly changed the estimation and simulation results.

4.3. Exogenous variables

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

We include the following social background characteristics of the 4,926 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),[15] number of siblings, and day of birth. The first five variables are standard and have also been included by other researchers (Cameron and Heckman 2001; Belzil and Poinas 2010). 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; Bedard and Dhuey 2006; Fumarco and Baert 2019).

Panel B of Table 3.2 reports descriptive statistics of these variables by student work experience during the period of secondary education. 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 school year. Pupils with student work experience have fewer siblings than pupils with no student work experience.

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 later employment outcomes, we control for this unemployment rate in the year and month, respectively, in which this outcome is realised.

[15] But Plug (2004) fills a gap in the literature by using a sample of adoptees to show that the impact of the schooling of the mother on the schooling of the child disappears when taking into account assortative mating and heritable abilities.

5. Method

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 during secondary education, 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 during secondary education on later employment outcomes in a direct effect (conditional on educational achievement and earlier employment outcomes) and an indirect effect via educational achievement and earlier post-graduate employment outcomes.

5.1. Econometric specification

Our model is a reduced-form 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 by, among others, Colding (2009), Colding et al. (2009), Belzil and Poinas (2010), Baert and Cockx (2013), Cockx et al. (2019), and Neyt et al. (2020). As previously mentioned, Hotz et al. (2002) and Ashworth et al. (2021) used this framework to tackle the endogeneity of student work and later employment outcomes. In addition, we propose a simulation strategy (in Section 5.3) that allows us to distinguish between the direct effect of student work on later employment outcomes and its indirect effect via educational attainment.

In line with the literature, our model is specified as a sequence of ordered logistic probabilities that each represent a particular outcome of the pupil's educational and early labour market career. As this modelling approach is not based on formal utility maximisation, it can be labelled as semi-structural. Therefore, we are not able to recover the present utility values related to each choice or to assess whether students internalize the positive impact of student employment on future labour market outcomes. However, as discussed by Belzil and Poinas (2010) or Heckman, Humphries, and Veramendi (2016), there are also several benefits to this semi-structural approach. First of all, it allows to take the dynamic nature of career decisions into account while not having to numerically solve value functions. Second, the estimates are open to a broader set op possible explanations as we do not have to make any assumptions about students' beliefs. For instance, while our estimates may be considered as being the result of perfectly forward looking behaviour, also other assumptions such as irrational choices or imperfect information may be taken into consideration.[16] Third, our approach also obviates the need to

[16] Nonetheless, in case one were willing to rely on more strict assumptions of utility maximising behaviour, one could interpret

rely on strong distributional assumptions.

We consider the following seven outcomes in our model: (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 pupil (and may affect all later outcomes), labelled in the literature as the initial conditions.

The set of values for a specific outcome,[17] denoted by C^O, is a set of ordinal numbers $C^O = \{0,1,\dots,n^O\}$, where the number of ordered choices that can be made for outcome O is n^O+ 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 school year (outcome value 2).[18] All other outcomes are binary in nature ($n^O = 1$).

The outcome value Y_i^O of an individual i with respect to outcome O is supposed to be determined by the following underlying process:

$$Y_i^O = c \in C^O \quad \text{if} \quad \omega_c^O < \widetilde{Y}_i^O \leq \omega_{c+1}^O,$$

where $\widetilde{Y}_i^O$ is a latent variable for outcome O, and ω_c^O and ω_{c+1}^O are threshold values that determine the ordered outcome value ($\omega_0^O \equiv -\infty$ and $\omega_{n^O+1}^O \equiv +\infty$). In line with the literature, we approximate this $\widetilde{Y}_i^O$ by a linear index:

$$\widetilde{Y}_i^O = Z_i\alpha^O + R_i^O\beta^O + V_i^O\gamma^O + \nu_i^O.$$

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 3.4.3. 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 ν_i^O is unobservable from the researcher's point of view.

Specifically, we assume that ν_i^O is characterised by the following factor structure:

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our model as being a reduced-form version of a structural model in the spirit of Eckstein and Wolpin (1999). In such a model, students trade off the time spent on various activities (working, studying, leisure) while taking into account both their consumption values and their effects on human capital accumulation (and, therefore, also future labour market outcomes).

[17] The terms "choices" and "outcomes" are sometimes used interchangeably in the dynamic discrete choice literature. We prefer to use the latter term as our model is a reduced-form model that does not allow one to differentiate between outcomes that result from explicit (and unconstrained) choices and other outcomes (see also Belzil and Poinas, 2010).

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

$$\nu_i^O = \delta^O \eta + \varepsilon_i^O,$$

in which η is modelled as a random effect, independent of ε_i^O, and independent across people, which captures unobserved determinants of the outcomes in the model. While this random effect is assumed to be independent of Z_i and R_i^O [19], it is allowed to correlate with V_i^O and, therefore, captures potential selective entry into student jobs. The outcome-specific coefficient δ^O is normalised to 1 for the first modelled outcome. ε_i^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:

$$\Pr(Y_i^O = c | Z_i, R_i^O, V_i^O, \eta\,; \theta) = \frac{\exp(\omega_{c+1}^O - Z_i\alpha^O - R_i^O\beta^O - V_i^O\gamma^O - \delta^O\eta - \varepsilon_{i,c}^O)}{1 + \exp(\omega_{c+1}^O - Z_i\alpha^O - R_i^O\beta^O - V_i^O\gamma^O - \delta^O\eta - \varepsilon_i^O)}$$
$$- \frac{\exp(\omega_c^O - Z_i\alpha^O - R_i^O\beta^O - V_i^O\gamma^O - \delta^O\eta - \varepsilon_{i,c}^O)}{1 + \exp(\omega_c^O - Z_i\alpha^O - R_i^O\beta^O - V_i^O\gamma^O - \delta^O\eta - \varepsilon_i^O)}$$

in which we denote the vector of unknown parameters by θ. The likelihood contribution $\ell_i(Z_i, R_i^O, V_i^O, \eta\,; \theta)$ 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 Heckman and Singer (1984), we adopt a non-parametric discrete distribution for the unobserved random variable η. As argued by Hotz et al. (2002), this makes our estimator more robust as it avoids relying on strong distributional assumptions. 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:

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

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

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

To estimate the causal effect of student employment, this methodology relies primarily on the variation that is left after conditioning on the observable determinants and the unobservable component[20]. Of course, this requires the unobservable component to be correctly identified as well. As Cameron and Heckman (1998, 2001) and Hotz et al. (2002) show, this identification requires to solve an initial condition problem. Working while studying is to be considered as one of subsequent human

[19] The coefficients on these variables, which are not the focus of our study, are thus not to be interpreted causally.

[20] This is a similar assumption as in the case of matching estimators, except that our model also conditions on unobservables that affect both student employment and the outcomes (cf. Heckman and Navarro, 2007; Heckman, Humphries, and Veramendi, 2016). As an example that contributes to this residual variation, one could, for instance, think of an accidental offer to participate in a job while being in high school.

capital investments decisions that are potentially affected by correlated stochastic shocks. By starting our model at the age of 15, our initialisation is comparable to the one by Hotz et al. (2002) and Ashworth et al. (2021), who start their model at age 13 and age 16 respectively. Further, Hotz et al. (2002) condition on the educational outcomes at age 12, based on the argument that, due to US compulsory schooling and child labour laws, children have little discretion over their human capital decisions at younger ages. Even so, although similar arguments hold with respect to the Flemish context, one cannot exclude there to be some correlated stochastic shocks that affect both the outcomes prior to and after age 15 (cf. Keane et al., 2011). Therefore, we model school delay at age 15 as a function of delay already realised at the start of primary education.

Finally, to further reduce (and test for) the impact of potential misspecification in the unobserved heterogeneity component, we follow Heckman, Humphries, and Veramendi (2016) and Ashworth et al. (2021) by adding an exclusion restriction to our model. More specifically, delay at the start of primary education is included as explanatory variable in our initial equation only, as the effect of school delay on student employment is unlikely to depend upon whether it took place before or after the start of primary education. Indeed, if we include this variable in the (ordered) logit models for the later outcomes, the related coefficient is never statistically significant from zero. Moreover, including this variable for all models neither changes the coefficient estimates for the other variables nor affects the simulation results. These latter findings are reassuring as they do not indicate our main conclusions to be driven by our identifying assumptions.

5.2. Model selection

We estimated the coefficients for the model presented in the previous subsection with a maximum likelihood estimation following Gaure et al. (2007). Heterogeneity types were gradually added until the log-likelihood value of the model failed to increase.

Appendix Table 3.A reports the number of parameters, the log-likelihood, and the Akaike Information Criterion (AIC)[21] 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 Appendix Table 3.B. Unless otherwise stated, the simulations below are based on these parameter estimates.

The coefficient estimates in Appendix Table 3.B provide further evidence that controlling for unobserved heterogeneity is important. First, the proportion of each of the three heterogeneity types

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

is substantial (p_1 = 72.4%, p_2 = 22.4%, and p_3 = 5.3%).[22] 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 Appendix Table 3.B 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 school 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.

5.3. Simulation strategy

Based on the estimated parameters for our preferred model, we simulate student work during secondary education, educational achievement, and employment outcomes. To answer our research questions, we 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 3.5.1. 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.

[22] For instance, following the equation for $p_k(q)$, $p_2 = \exp(-1.174)/(\exp(0) + \exp(-1.174) + \exp(-2.618))$.

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.

5.4. Goodness of fit

In Appendix Table 3.C 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 95% confidence intervals of the simulated probabilities. Therefore, we conclude that our model captures the dynamic choices in student work, educational attainment, and later employment outcomes quite well.

5.5. Average treatment effects

To answer our research question, we calculated – following the simulation strategy presented in Subsection 3.5.3 – two series of average treatment effects: one for the treatment 'student work during summer' and one for the treatment 'student work during summer and school year'.

5.5.1. Average Treatment effects on the Treated (ATTs)

First, we calculated Average Treatment effects on the Treated (ATTs). For the ATTs, the treated are pupils who in the simulations (following Subsection 3.5.3) were assigned to the treatment group, i.e. pupils who in the simulations did some form of student work (either during only the summer or during both the summer and the school year). For these pupils, we simulated the counterfactual scenario in which they did not do student work by forcing the variable indicating student work to zero. Then, we simulated all further schooling and early labour market outcomes for these pupils in this counterfactual scenario of no student work and compare it with their factual simulated schooling and early labour market outcomes. As a result, the ATT for a particular outcome can be presented as follows:

$$\mathrm{ATT} = \frac{\text{average outcome across treated individuals}}{\text{average outcome across treated individuals, in the counterfacutal of no treatment}}.$$

If the ATT is above (below) 1, this means there is a positive (negative) effect of the treatment on the outcome of interest.

5.5.2. Average Treatment effects on the Non-Treated (ATNTs)

Second, we calculated Average Treatment effects on the Non-Treated (ATNTs). For the ATNTs, the non-treated are pupils who in the simulations (following Subsection 3.5.3) were not assigned to the treatment group, i.e. pupils who in the simulations did not do any form of student work. For these students, we simulated the counterfactual scenario in which they did do student work by forcing the variable indicating student work to one (for student work during summer) or two (for student work during summer and academic year). Then, we simulated all further schooling and early labour market outcomes for these pupils in this counterfactual scenario of student work and compare it with their factual simulated schooling and early labour market outcomes. As a result, the ATNT for a particular outcome can be presented as follows:

$$\mathrm{ATNT} = \frac{\text{average outcome across untreated individuals, in the counterfacutal of treatment}}{\text{average outcome across untreated ind.}}.$$

If the ATNT is above (below) 1, this means there is a positive (negative) effect of the treatment on the outcome of interest.

5.6. Total, direct, and indirect effects

For all schooling and labour market outcomes realised after the decision to do student work, we make a distinction between total effects, direct effects, and indirect effects.

For the total effects, we do not condition the denominator of the equations for the ATTs and the ATNTs on earlier outcomes as would be realised in the scenario of treatment (doing student work). As a consequence, the treatment impacts the outcomes of interest both directly (via the model's coefficients capturing the direct effect of student work) and indirectly (via the model's coefficients capturing the effect of earlier outcomes, which in turn were (potentially) affected by student work).[23] Therefore, these total effects can also be labelled as 'unconditional effects', i.e. effects without keeping former schooling and labour market outcomes fixed to those of the treatment group.

For the direct effects, in contrast, we do condition the denominators of the equations for the ATTs and the ATNT on earlier outcomes as would be realised in the scenario of treatment (doing student work). As a consequence, the treatment impacts the outcomes of interest only directly (via the model's coefficients capturing the direct effect of student work). Therefore, these direct effects can also be labelled 'conditional effects', i.e. effects while keeping former schooling and labour market outcomes fixed to those of the treatment group.

[23] 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 Appendix Table B (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).

The indirect effects are calculated as the average differences between the total effects and the direct effects over all draws of the simulations (*supra*, Subsection 3.5.3). The indirect effects capture the impact of the treatment through earlier schooling and labour market outcomes (via the model's coefficients capturing the effect of earlier outcomes, which in turn were (potentially) affected by student work).

6. Results

Table 3.3 presents the ATTs with respect to the two student work treatments.[24] First, Section I shows that the total effect of student work in secondary education (only during the summer or during both the summer and the school year) on secondary education graduation is virtually zero. So, we do not find evidence that time spent working crowds out time spent on activities that enhance educational performance. Second, in contrast, we find that pupils who worked as a student both during the summer and the academic year are 16.9%[25] 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 suggests that any positive effects on participation in tertiary education resulting from the alleviation of financial constraints is overpowered by negative effects due to pupils' more intense immersion into the labour market.

Third, we find a positive total effect of student work during secondary education 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 school 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), with the additive effect of work during the school year becoming rather limited (8.7%-7.0%=1.7%-points). 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

[24] Results do not substantially differ when estimating ATTs or ATNTs (see Appendix Table D).

[25] −16.9% = 0.831 − 1.

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 school 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 Appendix Table 3.B).

Overall, the measured total effects of student work during secondary education on educational achievement corroborate with the literature. More concretely, the ATTs on the educational outcomes are in line with the mostly non-positive effect presented by contributions focussing on the effect of student work on educational achievement (Eckstein and Wolpin 1999; Stinebrickner and Stinebrickner 2003; Joensen 2009; Buscha et al. 2012; Neyt et al. 2018). Also the measured positive effects on later labour market outcomes are consistent with some of the studies published earlier with respect to secondary education (see Table 3.1), while the pattern of diminishing returns over time is in line with the findings of Häkkinen (2006) for tertiary education. Remarkably however, these positive labour market effects were not identified by Hotz et al. (2002) and Ashworth et al. (2021), who relied on a methodology similar to ours; we return to this difference in results in the conclusion section.

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 3.5.2 – 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 school 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 school 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.[26] 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.[27]

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 school 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 Appendix Table 3.B, 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.

7. 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 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

[26] According to the coefficients in Panels C and E of Appendix Table B, 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 Appendix Table B, 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.

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

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 estimated return to student work in terms of employment chances was somewhat 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 were 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. Remarkably, our conclusions also differ from those of Hotz et al. (2002) and Ashworth et al. (2021), who relied on a similar methodology but found no or even negative effects of student work during secondary education. However, their focus was on a country with a different labour market context (US) and on a different outcome variable (wages). But also the observation that most of the students in Flanders undertake their jobs during the summer holiday may provide an explanation, as this type of student work is less likely to interfere with educational activities like learning and doing homework. Indeed, our finding that student work during the summer affects enrolment in tertiary education only when it is combined with work during the school year, is in line with this interpretation. Moreover, while we did find a larger effect on initial employment chances for a combination of work during the summer and the school year relative to summer work only, the additive effect of this combination turned out to have disappeared almost completely one year after graduation.

From a policy perspective, these results provide clear support for measures aimed at incentivising pupils to work during the summer. For student work during the school year in secondary education, meanwhile, the advice is less clear-cut given its negative effect on tertiary education participation; although we did not find the indirect effect of this lower participation to dominate the positive direct effect on employment, the literature provides compelling evidence that educational participation also generates a large range of non-market returns (Oreopoulos & Salvanes, 2011). Moreover, also during secondary education, there is more in life than working and learning. For the individual pupil, the value of working while studying should therefore not only be traded off against potential negative effects on educational outcomes, but also against the value of leisure time (Eckstein & Wolpin, 1999).

We end with pointing to some interesting avenues for future research. 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.[28] For instance, while our study confirmed student employment to have a non-positive impact on educational outcomes, we were unable to explain the exact mechanisms through which such non-positive impact manifests itself. While it could be explained by positive effects on affordability of further education through the earnings of student employment which in turn are offset by negative effects on skill accumulation at school, we were unable to directly examine such explanation. Similarly, the direct effect on employment we identified may be explained both by human capital accumulation and by signalling. While unravelling their exact relative importance seems difficult based on the method in our paper, this should be feasible by relying on other methodologies such as stated choice experiments or the estimation of more structural models. 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 dynamic effect of student work by quantitative aspects of student work experience (e.g. average hours per week), qualitative aspects of this experience (e.g. relation to field of study), and qualitative aspects of labour market outcomes (e.g. job match quality).

8. Declarations

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Conflicts of Interest: The authors declare that they have no conflicts of interest.

Ethical approval : This article does not contain any studies with human participants performed by any of the authors.

Availability of data an material: Our analysis is based on the SONAR-data. This data collection was sponsored by the Flemish Government in the framework of the Flemish Policy Research Centre on Study

[28] However, Baert et al. (2016) 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.

and School Careers (www.steunpuntssl.be). To get access to the data, external users have to send a motivated request to the Policy Research Centre on Educational Research (sono@ugent.be), which is the successor of the Policy Research Centre on Study and School Careers. A similar procedure can be used when researchers would like to replicate the results in the paper.

Code availability: Codes are made available for replication by sending an email to the corresponding author.

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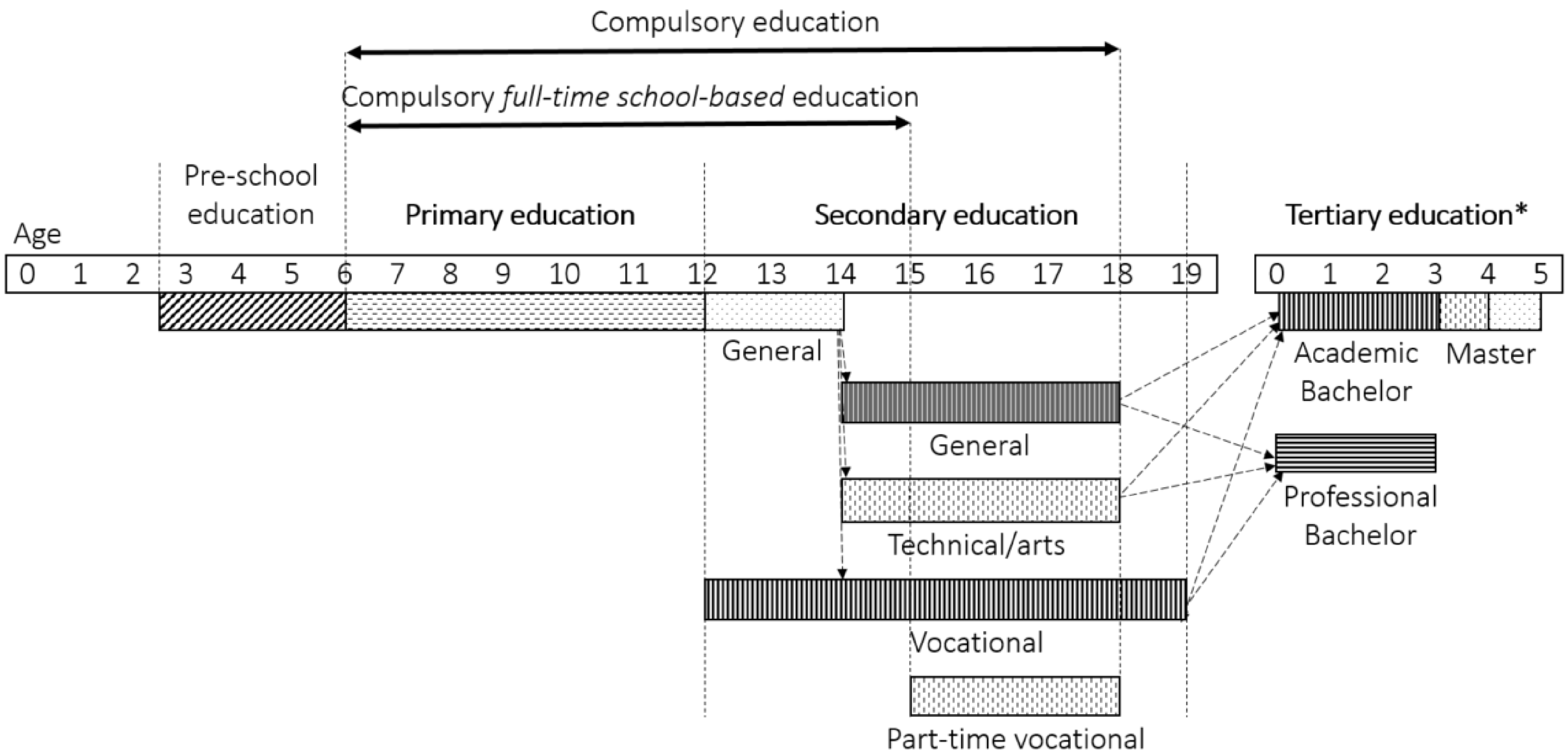
Figure 1. Organisation of education in Flanders.



Note. In tertiary education, the timeline indicates the programme duration in years.

Table 1. Schematic overview of the literature examining the effect of student work during secondary education on labour market outcomes.

(1) Study	(2) Country of analysis	(3) Main outcome variable(s)	(4) Main explanatory variable(s)	(6) Main methodological approach	(5) Main result(s)
Ashworth et al. (2021)	United States	Wages at age 29	Total years of SW in SE	DDC modelling	No effect or negative effect depending on the cohort
Hotz et al. (2002)	United States	Wages at ages 22 and 27	Total years of SW in SE	DDC modelling	No effect
Light (1999; 2001)	United States	Wages during 9 Y after LS	Total hours of SW in SE	IV approach	Positive effect.
Molitor and Leigh (2005)	United States	(Bi)annual wages after LS	Total hours of SW in SE	Parametric control for observables	Positive effect.
Parent (2006)	Canada	Wages in 1995 (age 22–24)	Any SW in SE	Selection model with exclusion restriction	No effect.
Ruhm (1997)	United States	Earnings 6–9 Y after LS	Hours of SW in years of SE	Selection model with exclusion restriction and IV approach	No effect or positive effect, depending on specification

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

Table 2. Summary statistics.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	I. Whole sample (N = 4,926)		II. Sample with no student work (N = 1,406)		III. Sample with student work during summer (N = 2,941)		IV. Sample with student work during summer and school year (N = 579)	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
A. Endogenous variables								
Delay at age 15	0.153	-	0.134	-	0.149	-	0.223	-
Student work experience during secondary education								
No student work	0.285	-	1.000	-	0.000	-	0.000	-
Student work during summer	0.597	-	0.000	-	1.000	-	0.000	-
Student work during summer and school year	0.118	-	0.000	-	0.000	-	1.000	-
Secondary education graduation	0.882	-	0.869	-	0.894	-	0.857	-
Tertiary education enrolment	0.687	-	0.703	-	0.703	-	0.566	-
Employed three months after leaving school	0.615	-	0.542	-	0.638	-	0.666	-
Employed one year after leaving school	0.847	-	0.801	-	0.866	-	0.854	-
Employed five years after leaving school	0.921	-	0.883	-	0.938	-	0.914	-
B. Exogenous variables								
Female gender	0.508	-	0.539	-	0.478	-	0.582	-
Migration background	0.052	-	0.076	-	0.035	-	0.074	-
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	-	0.015	-	0.015	-	0.016	-

Notes. See Section 3.4 for a description of the variables. For binary variables no standard deviations are presented.

Table 3. ATTs of student work experience during secondary education 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 school 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.

Appendix Table A. Model selection.

(1) # heterogeneity types (K)	(2) # parameters	(3) Log-likelihood	(4) Akaike Information Criterion
1	83	−14,847.803	29,861.606
2	91	−14,820.527	29,823.054
3	93	−14,817.501	**29,821.001**
4	95	−14,817.018	29,824.036
5	97	−14,817.018	29,828.036

Appendix Table B. Full estimation results.

	Coefficient (SE)
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)
Constant	1.263*** (0.236)
B. Outcome: Student work experience during secondary education	
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 during secondary education (reference)	
Student work during summer	0.123 (0.119)
Student work during summer and school year	−0.035 (0.178)
Constant	−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 during secondary education (reference)	
Student work during summer	−0.147 (0.126)
Student work during summer and school year	−1.030*** (0.231)

Constant	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 during secondary education (reference)	
Student work during summer	0.380*** (0.075)
Student work during summer and school year	0.623*** (0.120)
Secondary education graduation	0.309*** (0.112)
Tertiary education enrolment	0.191 (0.129)
Constant	−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 during secondary education (reference)	
Student work during summer	0.516*** (0.171)
Student work during summer and school 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)
Constant	−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 during secondary education (reference)	
Student work during summer	0.290 (0.190)
Student work during summer and school 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)
Constant	−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	−14,817.501
Akaike Information Criterion	29,821.001
N	4,926

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

Appendix Table C. 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 during secondary education (reference)		
Student work during summer	0.597	0.595 [0.575, 0.615]
Student work during summer and school 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]

Appendix Table D. ATTs versus ATNTs.

	(1)		(2)	
	Total effect			
	ATTs		ATNTs	
A. Treatment: Student work during summer				
Secondary education graduation	1.013	[0.983, 1.047]	1.013	[0.976, 1.051]
Tertiary education enrolment	0.989	[0.938, 1.042]	0.988	[0.927, 1.050]
Employed three months after leaving school	1.153***	[1.082, 1.232]	1.153***	[1.065, 1.249]
Employed one year after leaving school	1.070***	[1.029, 1.115]	1.067***	[1.023, 1.111]
Employed five years after leaving school	1.028**	[1.001, 1.061]	1.027	[0.994, 1.063]
B. Treatment: Student work during summer and school year				
Secondary education graduation	0.996	[0.937, 1.057]	1.008	[0.951, 1.069]
Tertiary education enrolment	0.831***	[0.714, 0.929]	0.806***	[0.664, 0.934]
Employed three months after leaving school	1.240***	[1.114, 1.389]	1.362***	[1.228, 1.497]
Employed one year after leaving school	1.087***	[1.015, 1.167]	1.124***	[1.061, 1.190]
Employed five years after leaving school	1.019	[0.969, 1.071]	1.038	[0.987, 1.085]

Notes. The presented statistics are simulated average treatment effects on the treated (ATTs) and average treatment effects on the non-treated (ATNTs) and 95% confidence intervals are given between brackets. * (**) ((***)) indicates significance at the 10% (5%) ((1%)) significance level. The following abbreviation is used: SE (secondary education).