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ABSTRACT

The Impact of Internship Experience during Secondary Education on Schooling and Labour Market Outcomes

The literature on workplace learning in secondary education has mainly focussed on vocational education programmes. In this study, we examine the impact of internship experience in secondary education on a student's schooling and early labour market outcomes, by analysing unique, longitudinal data from Belgium. To control for unobserved heterogeneity, we model sequential outcomes by means of a dynamic discrete choice model. In line with the literature on vocational education programmes, we find that internship experience has a positive effect on labour market outcomes that diminishes over time, although within the time window of our study, we find no evidence for a null or negative effect over time.

JEL Classification: I21, I26, J21, J24

Keywords: internship, transitions in youth, education, labour

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1 Introduction

One of the most important functions of an education system is to provide graduates a smooth transition from school to the labour market (OECD, 2013). Such smooth transition, however, is far from an empirical reality: as Figure 1 indicates, the youth unemployment rates within OECD countries consistently and substantially exceed their total unemployment rates (OECD, 2019a, 2019b).[1] Over the past decade, this distinction has proven especially pronounced in Belgium – the country of this study's analysis – where the youth unemployment rate was on average 2.7 times the total unemployment rate (compared to 2.1 in the other OECD countries). These numbers indicate that the transition from school to the labour market appears in need of substantial improvement.

< Figure 1 about here >

Past research has shown that improving this transition may be achieved by linking school more closely to the labour market. Indeed, multiple studies have substantiated the positive impact of workplace learning during secondary education, and particularly for vocationally oriented tracks, on early labour market outcomes (Arum & Shavit, 1995; Brunello & Rocco, 2015; Hampf & Woessman, 2017; Hanushek, Schwerdt, Woessmann, & Zhang, 2017; Neyt, Verhaest, & Baert, 2018 to name a few). Similar results have been found in certain studies examining the effect of internship experience during tertiary education (Gault, Redington, & Schlager, 2000; Nunley, Pugh, Romero, & Seals, 2016; Baert, Neyt, Siedler, Tobback, & Verhaest, 2019; Margaryan, Saniter, Schumann, & Siedler, 2019).[2]

Taking cues from human capital theory (Becker, 1964), the positive effect these studies describe is typically given a simple explanation: students with workplace experience have, by virtue of the broader

[1] The (youth) unemployment rate is the number of unemployed (15–24 year-olds) expressed as a percentage of the (youth) labour force (OECD, 2019a, 2019b). Unemployed people are those who report that they are without work, that they are available for work, and that they have taken active steps to find work in the last four weeks.

[2] This positive outcome was not confirmed in all studies (see Baert et al. (2019) for a schematic overview of the literature on this topic).

skillsets they are assumed to have acquired, an increased immediate productivity and can therefore immediately create added value for their employers, in turn improving their employability. In addition, relying on social network theory (Granovetter, 1973) as another explanation, it is argued that students with workplace experience have increased social capital which opens up opportunities that they would otherwise not have been aware of, both in the firm in which learning took place and outside of that firm.

However, a number of recent studies indicated that the short-term benefits of such work experience coincides with a long-term disadvantage on the labour market (Hampf & Woessman, 2017; Hanushek et al., 2017; Lavrijsen & Nicaise, 2017; Verhaest, Lavrijsen, Van Trier, Nicaise, & Omey, 2018). The theoretical reasoning behind this long-term negative effect is that the skills and knowledge students acquire through workplace experience are quickly outdated and are very susceptible to changes in labour demand. This is *a fortiori* true in present times, characterised by increased automation and digitisation (Hampf & Woessman, 2017). Furthermore, as students' time in school is limited, workplace learning comes at the cost of less general schooling, which may decrease students' potential for lifelong learning and, in turn, their long-term employment opportunities (Weber, 2014). Finally, although some observers point to the potentially positive effect of workplace learning on school persistence (Jørgensen, 2015; Kuczera, 2017), it has been empirically noted that workplace learning may reduce the likelihood of enrolling in and graduating from higher education (Pilz, 2007; Powell & Solga, 2011; Zilic, 2018). As a degree from higher education positively affects labour market outcomes, workplace learning may have a negative indirect effect – through worse higher education outcomes – on labour market outcomes in the long run.

As explained, previous studies on the effect of workplace learning on employability have examined both vocationally oriented tracks and internships. The main difference between these two types of workplace learning may be defined accordingly: in vocationally oriented tracks, the workplace learning component is at least (or even more) important than school-based learning in terms of hours spent, whereas internships usually represent a much smaller fraction of the overall time of workplace instruction. While most studies examine the impact of workplace learning during secondary education by examining vocationally oriented tracks, internship experience has mainly been examined in tertiary education. To date and to the extent of our knowledge, no studies have examined the causal impact of internship experience during secondary education. Results from such analyses would therefore provide novel insight, quantifying the effect of workplace learning during secondary education in a curriculum that is mostly school-based.

In the present study, we address this gap by examining the impact of internship experience during secondary education on both a student's schooling and labour market outcomes. More concretely, we examine this relationship by means of unique, longitudinal data with which we estimate a dynamic discrete choice model that jointly models students' schooling careers up to the decision to undertake an internship, the internship decision itself, students' schooling outcomes, and their early labour market outcomes. By introducing a random effect that impacts these sequentially modelled outcomes, we aim to tackle the problem of non-random selection into internships (*infra*, Section 4). In addition, this model allows us the ability to distinguish between the direct effect of internship experience on labour market outcomes and its indirect effects through potentially altered schooling outcomes. This latter contribution is especially important given the identified impact of workplace learning on schooling outcomes in existing literature (*supra*).

This study is structured as follows: in Section 2, we discuss the organisation of the education system in Flanders (the Northern, Dutch-speaking region of Belgium). In Section 3, we discuss the data. Then, in Section 4, we present the econometric model used to estimate the impact of internship experience on schooling and early labour market outcomes. In Section 5, we present and discuss the results of this estimation procedure. A final section completes this study with a brief conclusion that includes policy recommendations, limitations of this study, and (related) suggestions for future research.

2 Institutional setting

Education in Flanders is compulsory from 1 September of the year in which a child reaches age 6 until either 30 June of the year in which a child reaches age 18, or their 18th birthday – whichever comes first. Even though a regular student graduates from secondary education at age 18, this is not the case for a large number (approximately 30%) of Flemish students, because 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 in which there is no tracking. After graduating from primary education, students enter secondary education. Without grade retention before or during primary education, students start secondary education the year in which they reach age 12. Secondary education is divided into three tracks, summed up here from the 'highest' to the 'lowest' level: the general track, the technical or arts track, and the vocational track. After each school year, students may downgrade from one track to another.[3] For students in the general and the technical or arts tracks, secondary education comprises six consecutive years of study; this extends to seven years for those in the vocational track. From age 16 onwards, students have the possibility to enrol in part-time vocational education, in which they follow courses at school for several days a week, with the remaining days allocated for apprentice work with an employer. In this study, we exclude such students from our analyses, as we are interested in the effect of workplace learning in otherwise full-time school-based education programmes.

During the period under investigation in this study (1996–2009), certain technical and vocational track programmes included one or more mandatory internships with an employer.[4] Such internships

[3] Although students are technically allowed to 'upgrade' tracks, this never happens in practice.

[4] Since 2013, these internships have become mandatory by government decree in all programmes within the technical and vocational tracks.

could be done from the fourth year of secondary education onwards. These internships differ from the aforementioned apprenticeships in part-time vocational education because in internships the workplace component is both substantially smaller and more directed by the school (rather than by the employer).

Finally, students with a secondary education qualification from a full-time track (i.e. the general track, technical or arts track or full-time vocational track) can enrol directly, that is, without an entry exam, in tertiary education. They do so either at a college or a university, the latter being more prestigious. The only exception is for students who wish to study medicine, who are required to pass an entry exam.

3 Data

3.1 Sample

For this study, we used the SONAR data, which provided us with unique information on schooling and labour market outcomes for Flemish youths born in 1978 and 1980. For both cohorts, data was used for 3,000 individuals, collected through surveys taken at ages 23, 26, and 29. To be able to estimate our model with a homogeneous group of individuals, we deleted individuals from the dataset who (i) already had more than one year of study delay at the start of primary education (21 individuals), (ii) had special needs and were therefore in schools that provided special care (97 individuals), (iii) enrolled in part-time vocational education – as noted before – (406 individuals), and (iv) enrolled in the arts track, which only a few students choose (123 individuals). In addition, we deleted data from students (v) with erroneous or inconsistent data (470 individuals). Altogether, these deletions led to a final sample size of 4,883 individuals.

As internships were done in the technical and the vocational tracks (*supra*, Section 2), the analyses in Section 4 are limited to students in these tracks from the moment students were able to do an internship (i.e. the fourth year of secondary education) onwards. Therefore, the sample size for the outcomes after the outcome 'internship experience' (*infra*, Subsection 3.3) was reduced to 2,408.

3.2 Exogenous variables

When estimating the effect of internship experience on later schooling and labour market outcomes, we controlled for six strictly exogenous variables: a student's (i) gender, (ii) migration background, (iii) number of siblings, (iv and v) education level of the mother and father, and (vi) day of birth within the calendar year.

Summary statistics of these exogenous variables can be found in Panel A of Table 1.[5] In this table, we also make a comparison between students without internship experience (columns 3 and 4) and students with internship experience (columns 5 and 6). On average, students with internship experience were more often female, had more siblings, and had less educated parents.

< Table 1 about here >

Next to these background characteristics, we also included the district-level unemployment rate at the moment of each of the endogenously modelled outcomes (*infra*, Subsection 3.3). This allowed us to control for time- and district-varying labour market conditions and economic environments.

3.3 Endogenous variables

In our dynamic discrete choice model, we jointly estimated 11 sequential outcomes. The first five outcomes captured students' schooling careers, more specifically modelling students' (i) study delay at the start of primary education, (ii) study delay at the start of the fourth year of secondary education, (iii and iv) track choice at the start of the fourth year of secondary education, and (v) internship

[5] For reasons explained in the last paragraph of the previous subsection, also in Table 1 we restrict ourselves to students in the technical and the vocational tracks.

experience. We did not have data on when precisely students obtained internship experience, only that it occurred between the fourth year of secondary education (*supra*, Section 2) and the end of secondary education. Therefore, to preserve the sequentiality of our model – a necessary prerequisite for its identification – we modelled outcomes both strictly before and strictly after the possibility of doing an internship. For the outcomes strictly before, we modelled study delay and track choice at the start of the fourth year of secondary education. For the outcome strictly after, we modelled whether students (vi) graduated secondary education, which is the first of three outcomes capturing students' schooling outcomes. The remaining two were whether students (vii) enrolled in tertiary education and (viii) graduated tertiary education. Finally, as labour market outcomes, we modelled (ix–xi) whether students were employed three months, one year, and five years after leaving school. As additional analyses, for the labour market outcomes we modelled (ix–xi) whether students were employed *with a permanent contract* three months, one year, and five years after leaving school.

Panel B of Table 1 details summary statistics for the endogenous variables. Students with internship experience were more often delayed at the start of primary education and at the start of the fourth year of secondary education. Furthermore, they less often enrolled in tertiary education and therefore were less likely to graduate from it. Finally, concerning labour market outcomes, students with internship experience were more often employed (with a permanent contract) shortly after leaving school compared to students without internship experience; however, this effect reverses for the later labour market outcomes. This suggests that the findings from previous studies examining workplace learning that found evidence for short-term advantages but long-term disadvantages (*supra*, Section 1), may also hold true for internship experience.

However, as we have no data on when precisely during their schooling career students did internships (*supra*), we are unable to model outcomes between the moment students were able to start an internship (the fourth year of secondary education) and the end of secondary education. As a consequence, it might be that our variable indicating internship experience to some extent captures some students' downgrading from the technical track to the vocational track at the start of the fifth year of secondary education. Indeed, curricula in the vocational track focus more on preparing students for the labour market instead of for tertiary education, causing them to enrol in and graduate from tertiary education less often and increase their probability of being employed immediately after leaving school. In Subsection 5.2, we conduct two robustness analyses to address whether this played a salient role in explaining our results.

4 Method

In this section, we present the econometric model used to estimate the impact of internship experience during secondary education on a student's schooling and labour market outcomes. Our approach enables us to contribute methodologically to the literature on this topic in two ways. First, we aim to control in a new way for unobserved heterogeneity between students with and without internship experience. Second, we make a distinction between the direct and indirect effect of internship experience on labour market outcomes.

4.1 Dynamic discrete choice model

We build on dynamic discrete choice models used in existing literature examining the impact of various decisions and outcomes in education on labour market outcomes (Cameron & Heckman, 1998, 2001; Hotz, Xu, Tienda, & Ahituv, 2002; Baert & Cockx, 2013; Cockx et al., 2015; Neyt et al., 2018).

Our model is a sequence of binary probabilities. More specifically, we model the following 11 outcomes: (i) study delay at the start of primary education, (ii) study delay at the start of the fourth year of secondary education, (iii and iv) track choice at start of the fourth year of secondary education, (v) internship experience, (vi) secondary education graduation, (vii) tertiary education enrolment, (viii) tertiary education graduation, (ix) employment three months, (x) one year, and (xi) five year after leaving school. As alternative labour market outcomes, we model whether students were employed *with a permanent contract* (ix) three months, (x) one year, and (xi) five year after leaving school. See also Figure 2 for a schematic overview of this model.

< Figure 2 about here >

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. All outcomes are binary in nature, so that $n^O = 1$.

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

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

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

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

In this equation, Z_i is a vector representing the exogenous variables as observed for individual i, and R_i^O captures the district-level unemployment rate at the moment of outcome O, both of which were described in Subsection 3.2. Term V_i^O is the vector of endogenous outcomes that are realised before outcome O, which were described in Subsection 3.3. Terms 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:

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

in which δ_k^O is an outcome-specific random effect, independent of $\varepsilon_{i,c}^O$, and independent across people, which captures unobserved determinants of the outcomes in the model. $\varepsilon_{i,c}^O$ is the independent and identically distributed (i.i.d.) error term, which is logistically distributed.

Consequently, we can write the probability of a particular outcome value as follows:

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

in which we denote the vector of unknown parameters by ϑ. The likelihood contribution $\mathrm{l_i}(\mathrm{Z_i}, \mathrm{R_i^O}, \mathrm{V_i^O}, \delta_k^O; \vartheta)$ for any sampled individual, conditional on the unobservable δ_k^O, is then constructed by the product of the probabilities of the choices realised in the data for the 11 modelled outcomes.

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

$$\mathrm{p_k(q)} = \frac{\exp(\mathrm{q_k})}{\sum_{j=1}^{K}\exp(\mathrm{q_j})} \quad \text{with} \quad \mathrm{k} = 1, 2, \ldots, \mathrm{K}\,;\, \mathrm{q} \equiv [\mathrm{q_1}, \mathrm{q_2}, \ldots, \mathrm{q_K}]' \quad \text{and} \quad \mathrm{q1} = 0. \quad (5)$$

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

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

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. study delay at the start of primary education, is free of selection. This means that δ_k^O should be independent of $\mathrm{Z_i}$ and $\mathrm{R_i^O}$.

4.2 Model selection

The econometric model was estimated by maximum likelihood, following Gaure, Røed, and Zhang (2007). We started with a model without heterogeneity types (K = 1), before gradually adding heterogeneity types to the model. The model with the best (i.e. lowest) Akaike Information Criterion (AIC) was selected. Table A–1 in the Appendix shows the AIC values for all estimated models. The model with three heterogeneity types (K = 3) had the lowest AIC and is therefore our preferred model.

The full estimation results of our preferred model are represented in Table A–2 in the Appendix. The coefficient estimates provide evidence that controlling for unobserved heterogeneity is important. First, the proportion of each of the three heterogeneity types is substantial (p1 = 52.2%, p2 = 28.1%, and p3 = 19.7%).[6] Second, many of the parameters of the unobserved heterogeneity distribution (i.e. the δ_k^O's) are highly significantly different from 0.

4.3 Simulation strategy

Based on the preferred model's parameters (K = 3), we simulated schooling careers, schooling outcomes, and labour market outcomes. To answer our research questions, we ran these simulations under different (counter)factual scenarios regarding internship experience.

For each analysis, we randomly drew 999 vectors from the asymptotic normal distribution of the preferred model's parameters. Subsequently, in each of the 999 draws, the parameters were used to calculate the probabilities associated with each heterogeneity type. These probabilities were then used to assign a heterogeneity type to each pupil in the sample randomly. 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 was simulated for each pupil in the sample (for each draw).

More concretely, each outcome was simulated sequentially based on its logit specification reported in Subsection 4.1. These specifications yielded, for each individual in each draw, a probability for each potential outcome value. These probabilities were then translated to segments on the unit interval. To determine the particular outcome value for each individual in each draw, a number was generated from the standard uniform distribution. The outcome value assigned to the individual depended on the

[6] For example, following equation (5), p2 = exp(−0.621)/(exp(0) + exp(−0.621) + exp(−0.973)).

segment in which this random number fell. Once an outcome was assigned, it was saved and conditioned upon for the subsequent outcomes.

4.4 Goodness of fit

As Figure 3 displays, the simulated probabilities were closely distributed around the actual probabilities as observed in the data. In fact, the simulated probabilities never differed from the actual probabilities at the conventional confidence levels, i.e. up to 10% (see Table A–3 in the Appendix). This provides evidence for our model's strong ability to both capture and simulate the data very well.

< Figure 3 about here >

4.5 Average Treatment Effects

In the results section, we report Average Treatment Effects (ATEs) – the treatment in our case being internship experience. To answer our research questions, we calculated ATEs under (counter)factual scenarios with respect to internship experience.

The ATEs were calculated as follows:

$$\text{ATE} = \frac{\text{average outcome across treated individuals}}{\text{average outcome across untreated individuals}}. \qquad (7)$$

For each parameter draw, the numerator reflects the average outcome in case of treatment for all individuals, i.e. the factual simulated outcome for the individuals assigned to the treatment and the counterfactual simulated outcome for individuals not assigned to the treatment; for the latter group, we forced the dummy variable indicating treatment to '1'. The denominator reflects the average outcome in case of no treatment for all the individuals, which looks conversely, i.e. the factual simulated outcome for the individuals not assigned to the treatment and the counterfactual simulated outcome for individuals assigned to the treatment; for the latter group we forced the dummy variable indicating treatment to '0'.

If the ATE is above (below) 1, this means there is a positive (negative) effect of the treatment – internship experience – on the outcome of interest. In the results section, we discuss the distribution of these treatment effects, in other words we discuss their average over the 999 draws and their 95% confidence intervals.

4.6 Total and direct effects

For the labour market outcomes, we made a distinction between the total effect and direct effect of internship experience. For the total effect, our simulation strategy did not condition the denominator of Equation (7) on earlier outcomes, as would be realised in the scenario of no treatment (not doing an internship). Consequently, the treatment impacted the labour market outcomes both directly (via the model's coefficient capturing the direct effect of internship experience) and indirectly (via the model's coefficients capturing the effects of schooling outcomes, which in turn were (potentially) affected by internship experience). Conversely, for the direct effects, our simulation strategy <u>did</u> condition the denominator of Equation (7) on earlier outcomes as realised in the scenario of no treatment. Consequently, the treatment affected the labour market outcomes only directly (via the model's coefficient capturing the direct effect of internship experience on these outcomes).

5 Results

This section discusses the results of our estimation and simulation procedures. First, we compare results of a model without control for unobserved heterogeneity between students with and without internship experience (K = 1) to results of our preferred model in which we do control for this unobserved heterogeneity (K = 3). Second, we compare the total effect of internship experience on labour market outcomes to its direct effect (conditional on educational attainment). Third, we compare the impact of internship experience on two respective probabilities regarding students' employment status: those that result in a permanent contract, and those that do not. Finally, we discuss two robustness analyses.

5.1 Main results

Table 2 details the effect of internship experience both in a model without (K = 1) and with (K = 3) correction for unobserved heterogeneity, as discussed in Subsection 4.2. In the latter model, students with internship experience have a 40.6% higher probability of obtaining a secondary education qualification compared to students without internship experience. This is consistent with the idea that workplace learning may be a way to reduce school fatigue (Jørgensen, 2015; Kuczera, 2017). The effect of internship experience on 'secondary education graduation' is higher in the model with correction for unobserved heterogeneity than in the model without correction for unobserved heterogeneity, where a 24.7% higher probability was estimated. This suggests that students select negatively into internships, i.e. worse performing students more often chose to enrol in a curriculum including an internship. Concerning schooling outcomes in tertiary education, we find that students with internship experience were less likely to enrol in tertiary education compared to their peers without internship experience.[7] This is line with previous studies also reporting reduced enrolment in higher education for students with internship experience (Pilz, 2007; Powell & Solga, 2011; Zilic, 2018).

With respect to the labour market outcomes, in our model in which we control for unobserved heterogeneity, students with internship experience have heightened probabilities of employment both one year and five years after leaving school. In line with studies examining the impact of vocational education (*supra*, Section 1), this effect declines over time, i.e. from 17.8% higher chances of being

[7] Although in our preferred model this effect is rather imprecisely estimated, the direction of the effect undeniably points to a negative impact of internship experience on enrolment in tertiary education. A potential reason for this imprecise estimation is that the standard error for this outcome is dependent on the variance-covariance matrix and therefore also correlates with the explicit control for unobserved heterogeneity. The confidence intervals for the outcomes in tertiary education suggest that selection effects are important when looking at these outcomes. This is unsurprising, as factors like motivation and ability may both strongly impact the decision to do an internship and the decision to enrol in (and graduate from) tertiary education.

employed one year after leaving school to 10.7% higher chances of being employed five years after leaving school. However, in the time window of our model, we find no evidence for a negative, or even a non-significant, effect on the longer term. Also for the labour market outcomes, the effect of internship experience is more positive in the model in which we control for unobserved heterogeneity than in the model in which we do not, again suggesting a negative selection into internships.

The finding that the impact of internship experience on labour market outcomes merely diminishes in the first years after leaving school – rather than fading completely – differs from the finding in Neyt et al. (2018) – who use the same dataset – on the effects of apprenticeships in Flemish secondary education. In their study, the advantage in terms of employment chances was found to fade completely already one year after entering the labour market.

< Table 2 about here >

In Table 3, we compare the total effect of internship experience on labour market outcomes to its direct effect conditional on educational attainment. The direct effect of internship experience is substantial, increasing students' likelihood of employment one year and five years after leaving school by 15.9% and 15.2%, respectively. Therefore, the direct effect of internship experience proves the salient driver determining the total effect discussed above. As a result, we conclude that the effect of internship experience *per se* drives its impact on labour market outcomes and not its indirect effect through altered schooling outcomes. This can also be seen from the full estimation results detailed in Table A–2 in the Appendix. The coefficients for the internship experience variable are positive and highly significant when looking at their effect on employment outcomes one year and five years after leaving school (panel J and panel K of Table A–2 in the Appendix), while most coefficients related to the indirect effect are not.

< Table 3 about here >

In Table 4, we compare the outcome 'employed after leaving school' with the outcome 'permanent contract after leaving school'. For the latter outcome, the positive effect of internship experience is much greater compared to the former outcome; however, this effect likewise diminishes over time. Indeed, students with internship experience have a 78.7%, 39.1%, and 14.2% higher probability of securing a permanent contract three months, one year, and five years after leaving school than those without internship experience, respectively.[8] A potential explanation for the finding that results are stronger when looking at the probability of being employed *with a permanent contract* after leaving school may be found in screening theory (Stiglitz, 1975). Indeed, employers may use the internship period as a probationary period in which they screen students on their productivity and attitudes. In instances where this information is perceived as positive, employers might be more willing to offer these students a permanent contract compared to students who they were not able to screen by means of an internship.

< Table 4 about here >

5.2 Robustness analyses

As mentioned in Subsection 3.3, it might be that, to some extent, our variable indicating internship experience captures some students' downgrading from the technical track to the vocational track at the start of the fifth year of secondary education. To examine whether this downgrading potentially drives our results, we conducted two different robustness analyses. In the first robustness analysis, we replaced the variable indicating internship experience with a variable indicating downgrading from the technical to the vocational track at the start of the fifth year of secondary education. As can be seen from the coefficient estimates in column (ii) in Table A–4 in the Appendix, results from this analysis are substantially different from the results from our preferred model (in column (i)). This is a first indication that our internship variable indeed captures something different than track downgrading. Moreover, as

[8] Also for the outcome 'permanent contract after leaving school', results are more positive for the model in which we control for unobserved heterogeneity between student with and without internships experience compared to a model without this control (results available on request), again suggesting a negative selection into internships.

for the outcome 'secondary education graduation' the coefficient estimate of the robustness analysis goes in the opposite direction compared to the one of our preferred model, the effect of internship experience with respect to this outcome might therefore be seen as a lower bound. For the other outcomes of interest, the coefficient estimates of the robustness analysis are in the same direction but differ substantially in magnitude or statistical significance, further indicating that the results from our analyses in the previous subsection are not driven by track downgrade at the start of the fifth year of secondary education.

In the second robustness analysis, we estimated the impact of internship experience only for students in the vocational track. As this is the 'lowest' track in full-time school-based education, downgrading is unequivocally impossible and therefore the variable indicating internship experience cannot be affected by this track downgrading. Although the results from this analysis (reported in column (iii) in Table A–4 in the Appendix) differ in statistical significance from those of our preferred model due to a reduced sample size, they all go in the same direction, suggesting that we were indeed able to capture the impact of internship experience on our outcomes of interest in the previous subsection.

6 Conclusion

In this study, we used unique Belgian data to examine whether internship experience during secondary education had an effect on schooling outcomes and the transition from school to work. While in existing research the impact of internship experience had mainly been examined in tertiary education, our study is the first – to the extent of our knowledge – to examine the (causal) impact of internship experience during *secondary* education. In our analysis, we found that internship experience has a positive effect on the probability of obtaining a secondary education qualification, a finding consistent with the often-made claim that workplace learning may reduce school fatigue. However, we also found that internship experience in secondary education has a negative impact on a student's probability of enrolling in tertiary education. Concerning labour market outcomes, our results indicated that internship experience has a positive effect on the probability of being employed (with a permanent contract) after leaving school. Similar to previous research on workplace learning, we found that this short-term advantage of internship experience declines over time, although we found no evidence that in the time window of our model this effect fades out completely or even turns into a longer term disadvantage.

Our results provide useful insights for policy makers occupied with the organisation of workplace learning in secondary education. Although the benefit of internship experience diminishes over time, there remains a highly significant positive effect of internship experience on employment outcomes even five years after these students leave school. Therefore, while sharing with apprenticeships the advantage of leading to a smooth school to work transition, workplace learning by means of internships – where the workplace component is substantially smaller compared to apprenticeships – thus appears to be more effective in terms of maintaining employment chances over a longer period. Overall, this is consistent with the idea that integrating workplace learning in the curriculum of vocational programmes might be a good idea, as long as this integration does not come at a cost of the acquisition of more generic skills that are essential for one's long-term employability.

We end this study by summing up its main limitations, which are a consequence of the limitations tied to the data used in this study. A first limitation of the data is that they were from students who were enrolled in secondary education in the 1990s. As a consequence, results on internships experience may not easily extrapolate to the current state of the education system. However, using data from this period proved a necessary prerequisite for our research design as it allowed us to exploit a situation in which some programmes in the technical track and the vocational track had mandatory internships while other programmes did not. Such a situation cannot be exploited with more recent data, as now all programmes in the technical and vocational tracks in Flanders have mandatory internships by governmental decree (*supra*, Section 2).

A second limitation is that we were only able to examine labour market outcomes of students up to five years after they leave school. Ideally, future research would examine students' professional careers over a longer period to examine the impact of internship experience in secondary education on the even longer term.

A third limitation is that we were unable to examine whether students who do an internship with a certain employer stay with that employer at the start of their professional career. Indeed, we only possessed data on *whether* students did an internship and *whether* they were employed (with a permanent contract) after leaving school, not with which employer they did the internship/were employed. If future studies could find and exploit such data, it could be possible to examine to what extent it is social capital that drives the positive impact of internship experience on labour market outcomes and to what extent it is the (signal of) increased human capital through the skills and knowledge accumulated during the internship experience. Previous research has already taken steps in identifying the drivers of various decisions in education – such as student work (Van Belle et al., 2019) – by means of vignette experiments.

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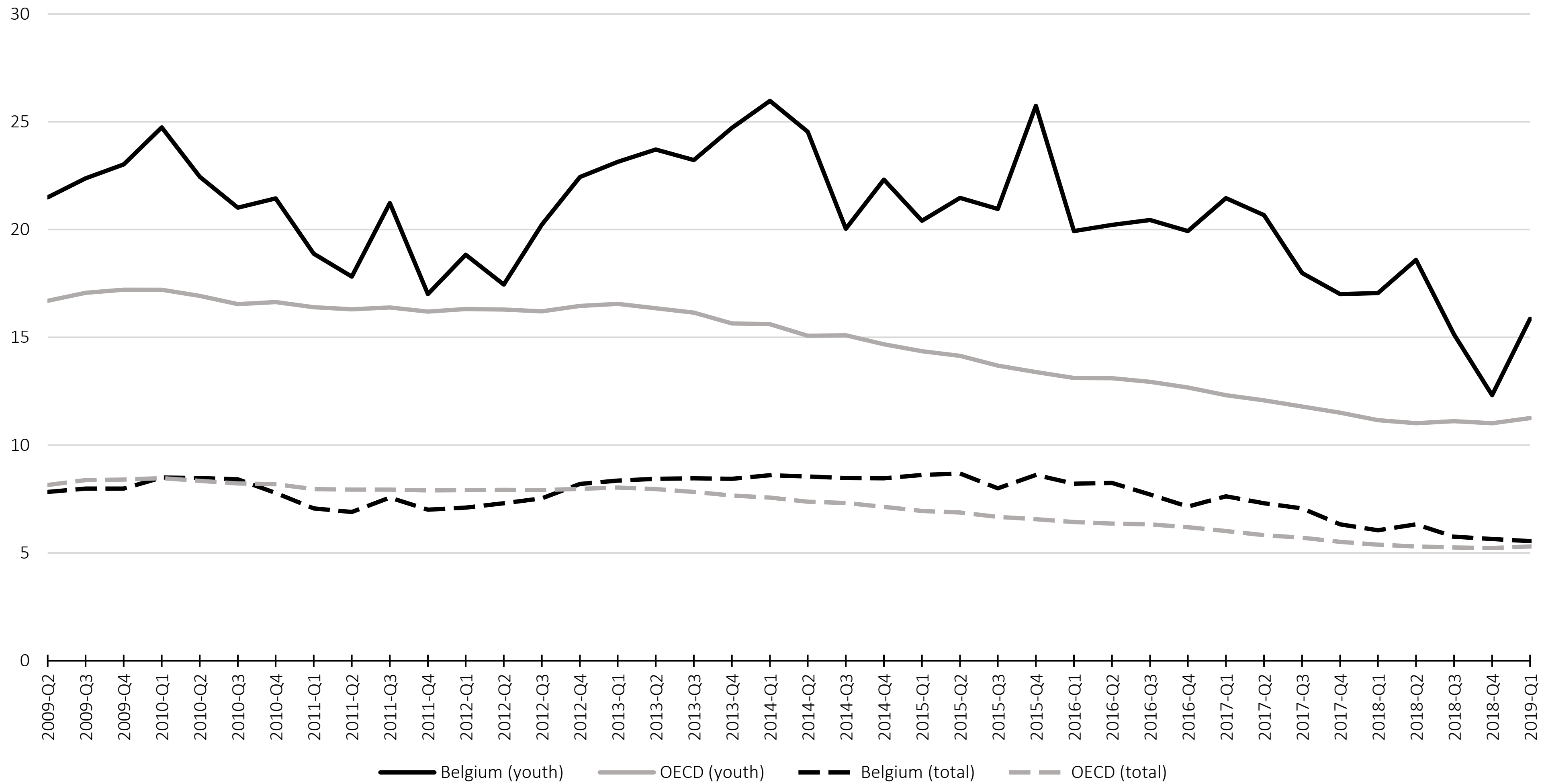
Figure 1. Youth and total unemployment rates in OECD countries and Belgium.

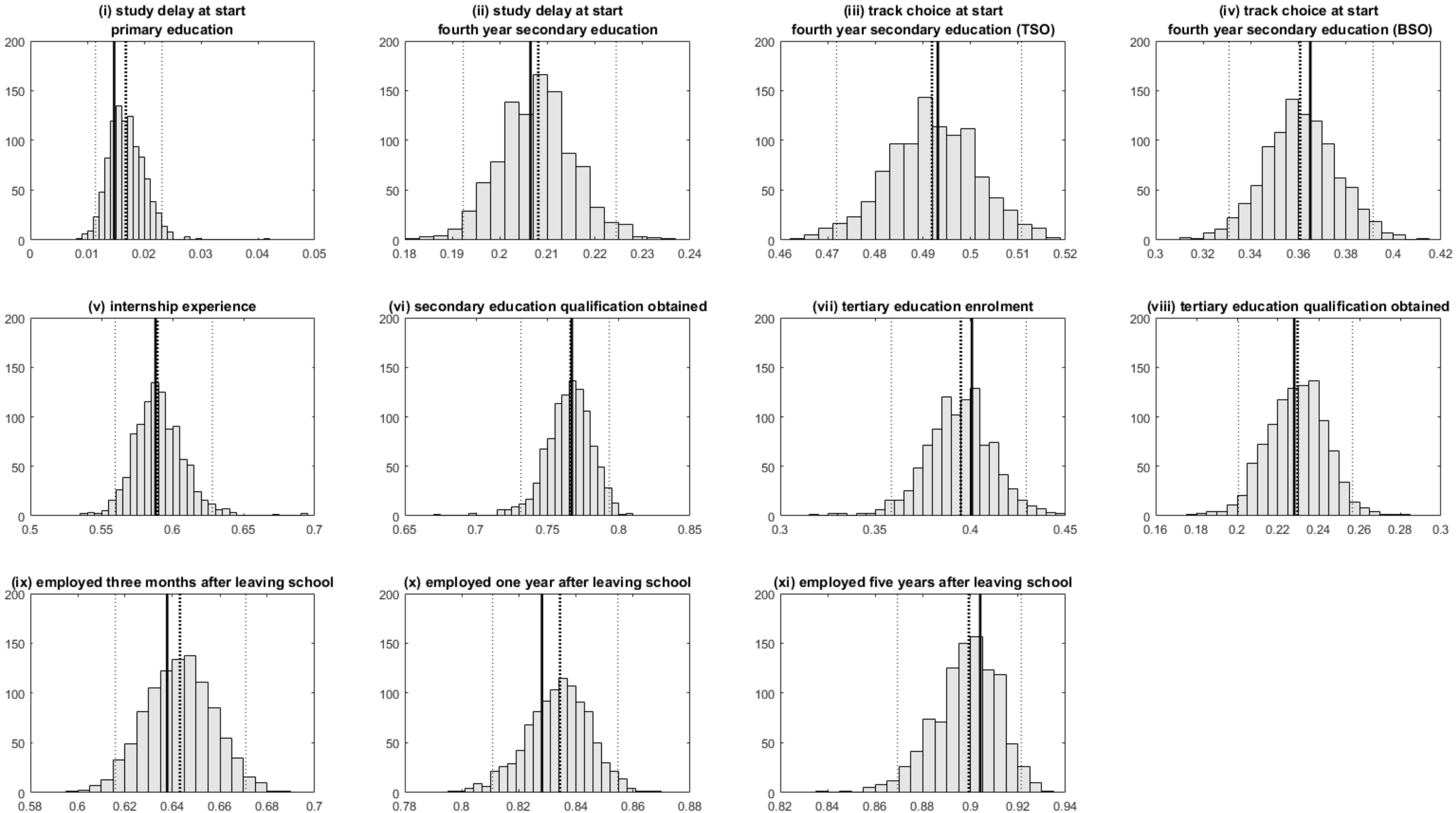


Notes. Source: OECD, 2019a, 2019b.

Figure 2. Schematic overview econometric model.

Note. The following abbreviations are used: PE (primary education), SE (secondary education), TE (tertiary education), mos. (months), yr. (year), and yrs. (years).

Figure 3. Goodness of fit.



Notes. The y-axis indicates how many times (on a total of 999) a particular probability (x-axis) was simulated. The full line indicates the actual probability, the dotted lines indicate the median (thick) and the 95% confidence interval (thin) of the simulated probabilities. From outcome (iv) on the model was simulated for students in the technical track and the vocational track only.

Table 1. Summary statistics.

	(1)	(2)	(3)	(4)	(5)	(6)
	I. Whole sample		II. Sample without internship experience		III. Sample with internship experience	
	(N = 2,408)		(N = 992)		(N = 1,416)	
	Mean	SD	Mean	SD	Mean	SD
A. Exogenous variables						
Female	0.463	0.499	0.392	0.488	0.513	0.500
Migration background	0.078	0.268	0.077	0.266	0.078	0.269
Number of siblings	1.667	1.463	1.581	1.390	1.727	1.509
Mother's education after primary education (years)	4.385	3.010	4.829	3.014	4.075	2.970
Father's education after primary education (years)	4.681	3.146	5.053	3.203	4.419	3.081
Day of birth within calendar year	185.819	103.771	184.804	103.827	186.530	103.763
B. Endogenous variables						
B.1. Variables related to selection into internships						
Study delay at start primary education	0.017	0.128	0.015	0.122	0.018	0.132
Study delay at start fourth year secondary education	0.339	0.473	0.284	0.451	0.377	0.485
Track choice at start fourth year secondary education						
General track	0.000	0.000	0.000	0.000	0.000	0.000
Technical track	0.313	0.464	0.240	0.427	0.179	0.383
Vocational track	0.180	0.384	0.046	0.209	0.185	0.388
B.2. Variables related to internships						
Internship experience	0.588	0.492	0.000	0.000	1.000	0.000
B.3. Variables related to schooling outcomes						
Secondary education qualification obtained	0.767	0.423	0.771	0.420	0.764	0.425
Tertiary education enrolment	0.401	0.490	0.601	0.490	0.261	0.439
Tertiary education qualification obtained	0.228	0.420	0.385	0.487	0.118	0.323
B.4. Variables related to labour market outcomes						
Employed three months after leaving school	0.638	0.481	0.634	0.482	0.640	0.480
Employed one year after leaving school	0.828	0.377	0.824	0.381	0.831	0.375
Employed five years after leaving school	0.904	0.295	0.915	0.278	0.896	0.305
Permanent contract three months after leaving school	0.326	0.469	0.296	0.457	0.347	0.476
Permanent contract one year after leaving school	0.513	0.500	0.490	0.500	0.529	0.499
Permanent contract five years after leaving school	0.777	0.416	0.780	0.415	0.775	0.418

Note. See Subsection 3.2 and Subsection 3.3 for a description of the mentioned variables.

Table 2. ATEs of internship experience on schooling and labour market outcomes: no correction versus correction for unobserved heterogeneity.

	(1)		(2)	
	Total effect Labour market outcome: employed after leaving school			
	No correction for unobserved heterogeneity (K = 1)		Correction for unobserved heterogeneity (K = 3)	
Secondary education qualification obtained	1.247***	[1.165, 1.338]	1.406***	[1.308, 1.565]
Tertiary education enrolment	0.596***	[0.529, 0.660]	0.136**	[0.033, 0.641]
Tertiary education qualification obtained	0.773***	[0.660, 0.891]	0.267*	[0.025, 1.116]
Employed three months after leaving school	1.051	[0.969, 1.142]	1.143*	[0.993, 1.281]
Employed one year after leaving school	1.055**	[1.005, 1.109]	1.178***	[1.108, 1.254]
Employed five years after leaving school	1.008	[0.970, 1.051]	1.107***	[1.061, 1.164]

Notes. The presented statistics are simulated Average Treatment Effects and 95% confidence intervals are given between brackets. * (**) ((***)) indicates significance at the 10% (5%) ((1%)) significance level.

Table 3. ATEs of internship experience on schooling and labour market outcomes: total versus direct effect.

	(1)		(2)	
	Correction for unobserved heterogeneity (K = 3) Labour market outcome: employed after leaving school			
	Total effect		Direct effect	
Employed three months after leaving school	1.143*	[0.993, 1.281]	1.124	[0.944, 1.291]
Employed one year after leaving school	1.178***	[1.108, 1.254]	1.159***	[1.073, 1.249]
Employed five years after leaving school	1.107***	[1.061, 1.164]	1.152**	[1.035, 1.271]

Notes. The presented statistics are simulated Average Treatment Effects and 95% confidence intervals are given between brackets. The direct effect is not presented with respect to the outcomes ‘Secondary education qualification obtained’, ‘Tertiary education enrolment’, and ‘Tertiary education qualification obtained’ as this direct effect equals the total effect (no conditioning on prior endogenous variables). * (**) ((***)) indicates significance at the 10% (5%) ((1%)) significance level.

Table 4. ATEs of internship experience on schooling and labour market outcomes: employed versus permanent contract after leaving school.

	(1)	(2)
	Correction for unobserved heterogeneity (K = 3) Total effect	
	Employed after leaving school	Permanent contract after leaving school
Employed three months after leaving school	1.143* [0.993, 1.281]	1.787*** [1.411, 2.144]
Employed one year after leaving school	1.178*** [1.108, 1.254]	1.391*** [1.183, 1.615]
Employed five years after leaving school	1.107*** [1.061, 1.164]	1.142*** [1.050, 1.232]

Notes. The presented statistics are simulated Average Treatment Effects and 95% confidence intervals are given between brackets. * (**) ((***)) indicates significance at the 10% (5%) ((1%)) significance level.

Table A–1. Model selection.

(1) **# heterogeneity types (K)**	(2) **# parameters**	(3) **Log-likelihood**	(4) **Akaike Information Criterion**
1	132	−13,399.981	27,063.961
2	144	−13,331.935	26,951.870
3	**156**	**−13,299.067**	**26,910.135**
4	168	−13,289.165	26,914.330
5	180	−13,281.696	26,923.392

Note. These are the results for the model with labour market outcomes 'employed after leaving school'. Also for the labour market outcomes 'permanent contract after leaving school' a model with three heterogeneity types minimises AIC.

Table A–2. Full estimation results of the preferred model (K = 3).

A. Outcome: study delay at start primary education		
Female gender	−0.075	(0.280)
Migration background	1.280**	(0.498)
Number of siblings	0.030	(0.109)
Mother’s education after primary education (years)	−0.001	(0.064)
Father’s education after primary education (years)	0.005	(0.051)
Day of birth within calendar year	0.005***	(0.001)
Unemployment rate	0.022	(0.077)
Intercept	−5.828***	(1.277)
B. Outcome: study delay at start fourth year secondary education		
Female gender	−0.614***	(0.079)
Migration background	0.611***	(0.158)
Number of siblings	0.118***	(0.028)
Mother’s education after primary education (years)	−0.092***	(0.015)
Father’s education after primary education (years)	−0.058***	(0.014)
Day of birth within calendar year	0.002***	(0.000)
Unemployment rate	0.019	(0.013)
Study delay at start primary education	2.839***	(0.342)
Intercept	−1.140***	(0.235)
C. Outcome: track choice at start fourth year secondary education – technical or vocational track		
Female gender	−0.498***	(0.097)
Migration background	−0.531**	(0.264)
Number of siblings	0.086**	(0.041)
Mother’s education after primary education (years)	−0.230***	(0.024)
Father’s education after primary education (years)	−0.239***	(0.022)
Day of birth within calendar year	0.001***	(0.000)
Unemployment rate	0.028*	(0.015)
Study delay at start primary education	1.294	(0.895)
Study delay at start fourth year secondary education	1.931***	(0.208)
Intercept	2.479***	(0.377)
D. Outcome: track choice at start fourth year secondary education – vocational track		
Female gender	0.317***	(0.111)
Migration background	0.071	(0.236)
Number of siblings	0.133***	(0.042)
Mother’s education after primary education (years)	−0.175***	(0.022)
Father’s education after primary education (years)	−0.126***	(0.021)
Day of birth within calendar year	0.000	(0.001)
Unemployment rate	0.002	(0.018)
Study delay at start primary education	−0.830	(0.592)
Study delay at start fourth year secondary education	0.941***	(0.123)
Intercept	0.575	(0.307)
E. Outcome: internship experience		
Female gender	0.903***	(0.197)
Migration background	−0.971***	(0.300)
Number of siblings	−0.007	(0.059)
Mother’s education after primary education (years)	0.023	(0.035)
Father’s education after primary education (years)	0.059*	(0.032)
Day of birth within calendar year	0.002*	(0.001)

Unemployment rate	0.014	(0.029)
Study delay at start primary education	3.617***	(1.203)
Study delay at start fourth year secondary education	−0.605***	(0.195)
Track choice: vocational track	5.846***	(1.062)
Intercept	−5.005***	(1.185)
F. Outcome: secondary education qualification obtained		
Female gender	0.432**	(0.177)
Migration background	0.185	(0.368)
Number of siblings	−0.046	(0.063)
Mother's education after primary education (years)	−0.029	(0.035)
Father's education after primary education (years)	0.062*	(0.034)
Day of birth within calendar year	0.001	(0.001)
Unemployment rate	−0.010	(0.033)
Study delay at start primary education	−1.144	(0.817)
Study delay at start fourth year secondary education	−0.385**	(0.191)
Track choice: vocational track	−8.124***	(1.249)
Internship experience	4.620***	(0.824)
Intercept	4.242***	(1.253)
G. Outcome: tertiary education enrolment		
Female gender	0.973***	(0.134)
Migration background	−0.030	(0.279)
Number of siblings	0.049	(0.050)
Mother's education after primary education (years)	0.051**	(0.024)
Father's education after primary education (years)	0.112***	(0.023)
Day of birth within calendar year	0.002***	(0.001)
Unemployment rate	0.033	(0.023)
Study delay at start primary education	1.342	(1.044)
Study delay at start fourth year secondary education	−0.296**	(0.141)
Track choice: vocational track	1.421	(1.721)
Internship experience	−4.737***	(1.734)
Intercept	−0.541	(0.336)
H. Outcome: tertiary education qualification obtained		
Female gender	0.526***	(0.148)
Migration background	−0.415	(0.424)
Number of siblings	0.112**	(0.054)
Mother's education after primary education (years)	0.005	(0.030)
Father's education after primary education (years)	0.056**	(0.027)
Day of birth within calendar year	0.001	(0.001)
Unemployment rate	−0.128***	(0.046)
Study delay at start primary education	0.325	(0.715)
Study delay at start fourth year secondary education	−0.725***	(0.177)
Track choice: vocational track	1.237	(1.605)
Internship experience	−3.033*	(1.642)
Intercept	0.715*	(0.402)
I. Outcome: employed three months after leaving school		
Female gender	−0.565***	(0.096)
Migration background	−0.673***	(0.195)
Number of siblings	−0.041	(0.036)
Mother's education after primary education (years)	0.005	(0.019)

Father's education after primary education (years)	−0.038**	(0.018)
Day of birth within calendar year	0.000	(0.000)
Unemployment rate	−0.099***	(0.021)
Study delay at start primary education	−0.465	(0.451)
Study delay at start fourth year secondary education	−0.064	(0.104)
Track choice: vocational track	−0.205	(0.321)
Internship experience	0.400	(0.286)
Secondary education qualification obtained	0.144	(0.213)
Tertiary education enrolment	−0.516***	(0.141)
Tertiary education qualification obtained	0.746***	(0.147)
Intercept	1.976***	(0.361)
J. Outcome: employed one year after leaving school		
Female gender	−0.614***	(0.146)
Migration background	−0.323	(0.278)
Number of siblings	−0.062	(0.051)
Mother's education after primary education (years)	−0.006	(0.028)
Father's education after primary education (years)	−0.039	(0.027)
Day of birth within calendar year	−0.002**	(0.001)
Unemployment rate	−0.156***	(0.031)
Study delay at start primary education	−0.838	(0.773)
Study delay at start fourth year secondary education	0.112	(0.158)
Track choice: vocational track	−1.445***	(0.459)
Internship experience	1.471***	(0.417)
Secondary education qualification obtained	−0.234	(0.343)
Tertiary education enrolment	−0.210	(0.209)
Tertiary education qualification obtained	1.315***	(0.261)
Employed three months after leaving school	2.360***	(0.157)
Intercept	2.995***	(0.533)
K. Outcome: employed five years after leaving school		
Female gender	−0.861***	(0.254)
Migration background	−0.715*	(0.406)
Number of siblings	−0.231***	(0.067)
Mother's education after primary education (years)	0.078*	(0.044)
Father's education after primary education (years)	−0.042	(0.044)
Day of birth within calendar year	0.001	(0.001)
Unemployment rate	−0.081	(0.068)
Study delay at start primary education	−2.159	(2.051)
Study delay at start fourth year secondary education	0.082	(0.254)
Track choice: vocational track	−3.039***	(1.067)
Internship experience	2.534**	(1.000)
Secondary education qualification obtained	−1.383	(0.978)
Tertiary education enrolment	0.205	(0.401)
Tertiary education qualification obtained	1.129*	(0.678)
Employed three months after leaving school	0.301	(0.279)
Employed one year after leaving school	1.047***	(0.284)
Intercept	4.655***	(1.271)
L. Unobserved heterogeneity distribution		
δ_2^1: Study delay at start primary education	−1.305	(0.903)
δ_2^2: Study delay at start fourth year secondary education	0.463***	(0.116)

δ_2^3: Track choice: technical or vocational track	0.090	(0.265)
δ_2^4: Track choice: vocational track	−2.280***	(0.307)
δ_2^5: Internship experience	6.323***	(1.081)
δ_2^6: Secondary education qualification obtained	−6.674***	(1.291)
δ_2^7: Tertiary education enrolment	3.422**	(1.728)
δ_2^8: Tertiary education qualification obtained	2.443	(1.655)
δ_2^9: Employed three months after leaving school	−0.544*	(0.319)
δ_2^{10}: Employed one year after leaving school	−1.579***	(0.464)
δ_2^{11}: Employed five years after leaving school	−3.263***	(1.079)
q_2	−0.621***	(0.104)
δ_3^1: Study delay at start primary education	1.145**	(0.470)
δ_3^2: Study delay at start fourth year secondary education	−0.739***	(0.231)
δ_3^3: Track choice: technical or vocational track	−5.103***	(0.580)
δ_3^4: Track choice: vocational track	3.957	(13.778)
δ_3^5: Internship experience	−5.331***	(1.995)
δ_3^6: Secondary education qualification obtained	2.832**	(1.401)
δ_3^7: Tertiary education enrolment	−5.192	(14.722)
δ_3^8: Tertiary education qualification obtained	−4.446	(99.671)
δ_3^9: Employed three months after leaving school	−1.283	(0.994)
δ_3^{10}: Employed one year after leaving school	1.189	(0.869)
δ_3^{11}: Employed five years after leaving school	6.370	(18.743)
q_3	−0.973***	(0.167)
N	4,883	
# heterogeneity types (K)	3	
# parameters	156	
Log-likelihood	−13,299.067	
Akaike Information Criterion	26,910.135	

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]
Study delay at start primary education	0.015	0.017 [0.012; 0.023]
Study delay at start fourth year of secondary education	0.206	0.208 [0.192; 0.225]
Track choice at start fourth year secondary education – technical of vocational track	0.493	0.492 [0.472; 0.511]
Track choice at start fourth year secondary education – vocational track	0.365	0.361 [0.331; 0.391]
Internship experience	0.588	0.591 [0.560; 0.628]
Secondary education qualification obtained	0.767	0.765 [0.731; 0.793]
Tertiary education enrolment	0.401	0.394 [0.358; 0.429]
Tertiary education qualification obtained	0.228	0.229 [0.201; 0.257]
Employed three months after leaving school	0.638	0.643 [0.616; 0.671]
Employed one year after leaving school	0.828	0.834 [0.811; 0.855]
Employed five years after leaving school	0.904	0.898 [0.869; 0.921]

Note. * (**) ((***)) indicates a significant difference between the actual and simulated probabilities at the 10% (5%) ((1%)) significance level.

Table A–4. Robustness analyses.

Impact of treatment on …	(i) Preferred model		(ii) Track downgrade		(iii) Vocational track only	
… secondary education graduation	4.620***	(0.824)	−0.607	(0.552)	2.975***	(0.389)
… tertiary education enrolment	−4.737***	(1.734)	−1.817**	(0.768)	−1.360	(0.897)
… tertiary education graduation	−3.033*	(1.642)	−1.001	(1.382)	/	
… employment three months after leaving school	0.400	(0.286)	−0.030	(0.343)	0.583**	(0.284)
… employment one year after leaving school	1.471***	(0.417)	0.496	(0.471)	0.415	(0.303)
… employment five years after leaving school	2.534**	(1.000)	0.846	(0.694)	0.324	(0.595)

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