

# The Impact of Internship Experience on Schooling and Labour Market Outcomes<sup>a</sup>

By Brecht Neyt,<sup>b</sup> Dieter Verhaest,<sup>c d</sup> Lorenzo Navarini,<sup>e</sup> and Stijn Baert<sup>f</sup>

Published in *CESifo Economic Studies*

## Abstract

We examine the impact of internship experience during secondary education on students' schooling and early labour market outcomes by analysing unique, longitudinal data from Belgium. To control for unobservable differences between students with and students without internship experience, we estimate a dynamic discrete choice model. In line with literature on vocational education, we find that internship experience has a positive effect on one's employment chances up to five years after graduation. This positive effect is mainly explained by a positive direct employment effect. Although we also find a positive indirect employment effect through a higher chance to obtain a secondary education qualification, this is largely compensated by negative indirect effects through lower tertiary education attainment.

**Keywords:** internship; transitions in youth; education; labour.

**JEL codes:** I21; I26; J21; J24.

**Citation:** Neyt, B., Verhaest, D., Navarini, L., & Baert, S. (2022). The Impact of Internship Experience on Schooling and Labour Market Outcomes. *CESifo Economic Studies*, ifac001. <https://doi.org/10.1093/cesifo/ifac001>

---

<sup>a</sup> **Acknowledgements and funding.** This research was funded by the Flemish Authority within the frame of the Policy Research Centre on Educational Research (Steunpunt SONO).

<sup>b</sup> Ghent University; Brecht.Neyt@UGent.be

<sup>c</sup> KU Leuven, Ghent University, and GLO; Dieter.Verhaest@KULeuven.be

<sup>d</sup> **Corresponding author.** KU Leuven, Campus Brussels, Warmoesberg 26, 1000 Brussels, Belgium.

<sup>e</sup> KU Leuven. Lorenzo.Navarini@KULeuven.be

<sup>f</sup> Ghent University, University of Antwerp, Université catholique de Louvain, IZA, and GLO; Stijn.Baert@UGent.be.

# 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). However, such smooth transition is far from an empirical reality. As Figure 1 indicates, youth unemployment rates in OECD countries consistently and substantially exceed total unemployment rates (OECD 2019a, 2019b).<sup>1</sup> 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 an average of 2.1 in the other OECD countries). These numbers indicate that the transition from school to the labour market is 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 and Shavit 1995; Brunello and Rocco 2015; Hampf and Woessman 2017; Hanushek, Schwerdt, Woessmann and Zhang 2017; Neyt, Verhaest and Baert 2020). Similar results have been found in certain studies examining the effect of internship experience during tertiary education (Gault, Redington and Schlager 2000; Nunley, Pugh, Romero and Seals 2016; Baert, Neyt, Siedler, Tobback and Verhaest 2021; Margaryan, Saniter, Schumann and Siedler 2020).<sup>2</sup>

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

---

<sup>1</sup> 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.

<sup>2</sup> This positive outcome was not confirmed in all studies (see Baert et al. (2021) 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, in line with theories of on-the-job screening (Stiglitz 1975) and signalling (Spence, 1973), internships may also allow one to reveal pre-existing abilities and skills that are less easily revealed through participation in school-based education. That way, internship experience may increase employment chances even without increasing human capital (*supra*). Finally, 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 the workplace 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 and Woessman 2017; Hanushek et al. 2017; Lavrijzen and Nicaise 2017; Verhaest, Lavrijzen, Van Trier, Nicaise and Omeij 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 and 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 argued that a stronger focus on workplace learning and vocational courses may reduce the likelihood of enrolling in and graduating from higher education (Pilz 2007; Powell and 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 is that in vocationally oriented tracks the workplace learning component is at least as (or even more) important than school-based learning in terms of hours spent, while 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 for Flanders (the Northern, Dutch-speaking region of Belgium), and estimate a dynamic discrete choice model that jointly estimates students' schooling careers up to the decision to undertake an internship, the internship decision itself, students' schooling outcomes, and their early employment chances. 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 to distinguish between the direct effect of internship experience on employment chances 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*).

In line with the literature on vocationally oriented tracks in secondary education and on internships in tertiary education, our results confirm that also internships in secondary education improve one's initial employment chances. Moreover, unlike some other studies on the effects of vocational education and workplace learning, we do not find this effect to completely fade out during the time window of observation. Our results also illustrate the importance to distinguish between direct and indirect effects of internship experience. Although we find its positive effect on employment to be mainly attributed to

a direct effect, internship experience is also found to generate indirect employment effects: a positive indirect effect through a higher chance to obtain a secondary education qualification levels out a negative indirect effect through lower tertiary education attainment.

The paper is structured as follows: in Section 2, we discuss the organisation of the Flemish education system in Flanders. 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 percent) 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.

< Figure 2 about here >

In Figure 2, we summarise the organisation of the Flemish educational system. 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. Students in the general and the technical or arts tracks have to pass six consecutive years of study to obtain a secondary education qualification; this extends to seven years for

those in the vocational track<sup>3</sup>. Students may downgrade from one track to another between the subsequent school years, except between the fifth and sixth year of study in secondary education for which this is not allowed.<sup>4</sup> From age 16 onwards (or from age 15 conditional on having completed already the first two years of secondary education), students have also the possibility to enrol in a separate part-time vocational education track, in which they follow courses at school for one or two days a week, with the remaining days allocated for apprentice work with an employer.

During the period under investigation in this study (1996–2009), certain (full-time) technical and vocational track programmes included one or more mandatory internships with an employer.<sup>5</sup> Such internships could be included in the programme from the fourth year of secondary education onwards, that is three or four years before students graduate from secondary education. As these internships are an integral part of the student's curriculum, they differ in a number of respects from the more voluntary internships that have become increasingly popular among tertiary education students (e.g. Jaeger et al., 2020)<sup>6</sup>. For instance, unlike what is the case for these voluntary internships, intra-curricular internships substitute away time devoted to classroom-based training. Moreover, although also the student may be involved in searching for an internship placement, the school bears the ultimate responsibility to find an internship placement that meets the minimum standards. Finally, obtaining a positive evaluation as an intern is usually a necessary (but insufficient) prerequisite to pass one's year of study. While most studies on the causal labour market effects of internships in the context of tertiary education have focussed on voluntary internships, a few have looked at mandatory internships as well. Overall, the evidence with regard to these types of internships is more mixed relative to voluntary internships (see Baert et al., 2021). For instance, while Margaryan et al. (2020) found clear positive effects of mandatory

---

<sup>3</sup> Also in the technical track, students may participate in an extra seventh year. However, passing this year is not required to obtain a secondary education qualification or to enroll in tertiary education for these students.

<sup>4</sup> Although students are technically also allowed to 'upgrade' tracks, this never happens in practice.

<sup>5</sup> Since 2013, these internships have become mandatory by government decree in all programmes within the technical and vocational tracks.

<sup>6</sup> For an evaluation of similar mandatory internships in tertiary education, see for instance Verhaest and Baert (2018) for Belgium and Margaryan et al. (2020) for Germany.

internships in German tertiary education, Verhaest and Baert (2018) did not find significant effects of these types of internships in Flemish tertiary education.

These mandatory internships also differ in several ways from the aforementioned apprenticeships in part-time vocational education. First of all there is the duration and intensity, which are substantially smaller for internships relative to apprenticeships. While pupils spend each week 60% to 80% of their learning time on the workplace in the apprenticeship systems, internships are often concentrated in a limited number of weeks and also differ in duration across the years of study. Secondly, while apprentices are usually employed with the same employer during the entire period of their training, the workplace training in the internship system is often spread over multiple employers. Third, internships are more directed by the school rather than by the employer as in the apprenticeship system. Fourth, internships mostly focus on practicing the vocational skills that have been acquired at school rather than on acquiring these vocational skills at the workplace itself as is the case for apprenticeships. Fifth, while internships are included in a subset of programmes within the vocational and technical tracks only and also schools have some freedom to include them in the curriculum, apprenticeships can be considered as being a defining characteristic of the part-time vocational track itself. Finally, also in terms of eligibility, they are clearly different. As internships are programmed from year four in secondary education onwards, eligibility is inherently restricted to those having passed the third year of secondary education. Eligibility to the apprenticeship programmes, meanwhile, is age-based rather than being dependent upon having passed a certain minimum number of years of study (unless one aims at participating already at age 15).

After having obtained a secondary education qualification from a full-time track (i.e. the general track, technical or arts track or full-time vocational track), students can enrol directly, that is, without an entry exam, in tertiary education. The only exception is for students who wish to study medicine, who are required to pass an entry exam. As this access to tertiary education does not apply to part-time vocational education, this defines an additional important difference between the apprenticeship and internship system. Tertiary education is either attended at a college or at a university, with programmes

at a college usually consisting of three years of study and programmes at a university taking at least four years of study<sup>7</sup>.

The effects of the part-time vocational programmes and apprenticeships in Flemish secondary education have already been evaluated in Neyt et al. (2020) based on a similar methodology and the same data. In line with the literature on workplace based learning, part-time vocational education programmes that were combined with four days of apprenticeship training per week were found to improve employment rates at the start of the career. However, these effects were found to diminish rather quickly over time and no evidence on (positive or negative) effects was found for programmes that consisted of three days of apprenticeship training per week only. In this paper, we turn our attention to the internship system, allowing us to evaluate the effect of a less-intensive workplace learning component in otherwise full-time school-based vocational or technical education programmes. Moreover, unlike the analysis of the part-time vocational system, our focus allows to assess whether workplace learning also affects one's chances to enrol in and obtain a tertiary education degree for reasons other than legal eligibility rules. As the way internships and apprenticeships are integrated in the Flemish education system is largely different, a simultaneous analysis of both systems would strongly complicate our modelling. Therefore, we exclude the students from the part-time vocational education system from our analyses.

### **3 Data**

#### **3.1 Sample**

For this study, we used the SONAR data, which provided us with unique information on schooling and

---

<sup>7</sup> Figure 2 describes the system as it was organised during the period under consideration. Nowadays, university programmes are usually subdivided in a bachelor's programme of three years of study and a subsequent master's programme of at least one year of study. Moreover, individuals that have finalised a bachelor's programme at a college now also have the option to enroll in a master's programme at university conditional on having completed a bridging programme that usually takes one year of study.



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, inconsistent, or incomplete data (470 individuals).<sup>8</sup> 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<sup>9</sup>. 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, (vi) birth year, and (v) day of birth within the calendar year.

---

<sup>8</sup> An example of obvious erroneous data are observations in which the student was in the fifth year of secondary education in year  $t$  but in the fourth year of secondary education in year  $t + 1$ , which is not possible. An example of inconsistent data are observations in which the student started tertiary education, without having completed secondary education in the data, which is not possible in Flanders. An example of incomplete data are students with only one observation. These students should not have been part of the data, but were so anyways.

<sup>9</sup> The data explicitly differentiate between internship experience and work experience in standard jobs.

Summary statistics of these exogenous variables can be found in Panel A of Table 1.<sup>10</sup> 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 experience. We did not have data on when precisely students obtained internship experience, only that it occurred between the start of 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

---

<sup>10</sup> 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.

school. While the focus of other studies is sometimes rather on early wages or earnings, we consider early employment chances to be a more relevant indicator of early labour market success in the Belgian context of high minimum wages and strong collective wage bargaining. As additional analyses, for the labour market outcomes we modelled in an analogous, parallel model (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 were less likely to graduate from it, conditional on starting 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 and Heckman 1998, 2001; Hotz, Xu, Tienda and Ahituv 2002; Baert and Cockx 2013; Cockx et al. 2015; Neyt et al. 2020).

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 3 for a schematic overview of this model.

< Figure 3 about here >

The choice set for a specific outcome, denoted by  $C^O$ , is a set of ordinal numbers:  $C^O = \{0, 1, \dots, n^O\}$ , 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:

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

where  $U_{i,c}^O$  is the latent utility of choice  $c$  for outcome  $O$ , and  $\omega_{c+1}^O$  and  $\omega_{c+1}^O$  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:

$$U_{i,c}^O = Z_i \alpha^O + R_i^O \beta^O + V_i^O \gamma^O + v_{i,c}^O. \quad (2)$$

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  $\alpha^O$ ,  $\beta^O$ , and  $\gamma^O$  are the vectors of associated parameters and  $v_{i,c}^O$  is unobservable from the researcher's point of view.

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

$$v_{i,c}^O = \eta \delta_k^O + \varepsilon_{i,c}^O, \quad (3)$$

in which  $\eta$  is a random effect, independent of  $\varepsilon_{i,c}^O$  and independent across people, which captures determinants that are unobserved and assumed to be independent of the observed exogenous variables  $Z_i$  and  $R_i^O$ .<sup>11</sup> The outcome-specific coefficients  $\delta_k^O$  are normalised to 1 for the first modelled outcome.  $\varepsilon_{i,c}^O$  is the independent and identically distributed (i.i.d.) error term and assumed to be logistically distributed.

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

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

---

<sup>11</sup> Due to this assumption, the coefficients of  $Z_i$  and  $R_i^O$  cannot be interpreted causally. Note that this is not a problem in the context of our paper given that these variables and their effects are not the focus of our analysis.

$$-\frac{\exp(\omega_c^0 - Z_i\alpha^0 - R_i^0\beta^0 - V_i^0\gamma^0 - \eta\delta_k^0 - \varepsilon_{i,c}^0)}{1 + \exp(\omega_c^0 - Z_i\alpha^0 - R_i^0\beta^0 - V_i^0\gamma^0 - \eta\delta_k^0 - \varepsilon_{i,c}^0)}$$

in which we denote the vector of unknown parameters by  $\vartheta$ . The likelihood contribution  $l_i(Z_i, R_i^0, V_i^0, \eta; \vartheta)$  for any sampled individual, conditional on the unobservable  $\eta$ , 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  $\eta$ . 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:

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

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

$$l_i(Z_i, R_i^0, V_i^0; \vartheta, q) = \sum_{k=1}^K p_k(q) l_i(Z_i, R_i^0, V_i^0, \eta_k; \vartheta). \quad (6)$$

As explained by Cameron and Heckman (1998, 2001) and Keane, Todd and Wolpin (2011), an initial conditions problem has to be solved to identify the causal effect. Acquiring internship experience is part of a broader educational decisions process with sequential decisions which are potentially affected by serially correlated shocks. Consequently, we have to make an assumption about when this educational process has been initialised. In our model this assumption is substantially weaker compared to assumptions made in many earlier studies using the same methodology (see, e.g., Hotz et al. 2002; Adda, Dustmann, Meghir and Robin 2010), as our estimation already starts very early in a student's educational career, i.e. at the start of primary education which occurs at age six and even then we already model some variation in the years of study delay.

## 4.2 Model selection

The econometric model was estimated by maximum likelihood, following Gaure, Røed and Zhang (2007). We gradually added heterogeneity types to the model, which we discuss in the next section. 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 ( $p_1 = 25.8\%$ ,  $p_2 = 21.4\%$ , and  $p_3 = 52.8\%$ ).<sup>12</sup> Second, many of the parameters of the unobserved heterogeneity distribution (i.e. the  $\eta_k$ 's and  $\delta_k^0$ '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

---

<sup>12</sup> For example, following equation (5),  $p_2 = \exp(-0.621)/(\exp(0) + \exp(-0.621) + \exp(-0.973))$ .

the standard uniform distribution. The outcome value assigned to the individual depended on the 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 4 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 percent (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 4 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:

$$ATE = \frac{\text{average outcome across all individuals in case of treatment}}{\text{average outcome across all individuals in case of no treatment}}. \quad (7)$$

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 percent 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 treatment (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 earlier outcomes, which in turn were (potentially) affected by internship experience). Therefore, these total effects can also be labelled as 'unconditional effects', i.e. effects without keeping earlier outcomes fixed to those of the treatment group.

Conversely, for the direct effects, our simulation strategy did condition the denominator of Equation (7) on earlier outcomes as realised in the scenario of 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 69.3 percent 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 24.2 percent 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 and to obtain a tertiary degree qualification compared to their peers without internship experience.<sup>13</sup> This is in line with Zilic (2018), who found some evidence on improved chances to obtain a university degree after a reform that extended the general curriculum in vocational programmes.

With respect to the labour market outcomes, according to our model in which we control for unobserved heterogeneity, students with internship experience have a 20.1 percent heightened probability of employment three months. In line with studies examining the impact of vocational education (*supra*, Section 1), this effect declines somewhat later on. However, in the time window of

---

<sup>13</sup> 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.

our model, this decline is rather small – from 21.8 percent to 17.6 percent between one and five years after leaving school – and 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 employment outcomes diminishes only slightly in the first years after leaving school seems to differ from the finding in Neyt et al. (2020) – 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. Note, however, that both studies differ with respect to the definition of the control group; while our study compares students with and without participation in internships within the same tracks, the Neyt et al. (2020) study rather compared those in the part-time vocational track with those in all other tracks. This complicates somehow a simple comparison of the estimated treatment effects across the two studies.

< 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 on the likelihood to be employed three months after leaving school is equal to 19.5 percent, which is close to its total effect. Moreover, while the estimated direct effects of internships are somewhat lower for the employment outcomes one and five years after leaving school, these direct effects for later employment outcomes represent the effects of internship experience net of the effects through earlier employment outcomes. As a result, we conclude that the effect of internship experience *per se* drives its impact on labour market outcomes rather than its indirect effect through altered schooling outcomes. As can be seen from the full estimation results detailed in Table A–2 in the Appendix, this negligible impact through altered schooling outcomes results from opposing effects; while the direct employment effects

of a higher likelihood to obtain a secondary qualification and a lower likelihood to enrol in tertiary education are positive<sup>14</sup>, this is compensated by a negative employment effect through a lower likelihood to obtain a tertiary education qualification.

< 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 also diminishes more rapidly over time. Indeed, students with internship experience have a 97.8 percent, 37.1 percent, and 19.7 percent higher probability of securing a permanent contract three months, one year, and five years after leaving school than those without internship experience, respectively.<sup>15</sup> Nonetheless, the latter effect remains strongly statistically significant and is still slightly above the effect on the probability of being employed *per se*. A potential explanation for the finding that the initial labour market effects are stronger when looking at the probability of being employed *with a permanent contract* after leaving school may be found in on-the-job screening models (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 immediately 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

---

<sup>14</sup> Note that the negative direct effect of tertiary education enrolment on employment does not encompass the effect of enrolment through a higher likelihood to obtain a tertiary education qualification. This negative direct effect may therefore reflect the effect of dropout from tertiary education.

<sup>15</sup> 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.

We also conducted several 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. Our first two robustness analyses examine whether this downgrading potentially drives our results. First, 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 for the outcomes 'secondary education graduation' and "employment five years after leaving school" the coefficient estimates of the robustness analysis go in the opposite direction compared to the ones of our preferred model, the effect of internship experience with respect to these outcome might therefore be seen as lower bounds. 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.

Next, we re-estimated our models by adding interactions between the internship variable and a number of social background indicators. As part of the return to internships may be attributed to

screening and networking effects, one may expect this effect to be stronger among individuals that have weaker social networks. However, as reported in Table A–5 in the Appendix, none of these estimated interactions were found to be statistically significant.

Finally, we conducted two robustness checks using indicators of job quality other than permanent contract. To this end, we exploited information on the individual’s first standard job<sup>16</sup>, for which more information on job quality is available in the data. In a first robustness check, we replaced the three employment outcomes in our model by a dummy that indicates whether the first job was at least a medium-skilled job<sup>17</sup>. As reported in Table 5, also this analysis suggests internships to improve one’s labour market outcomes. In a second check, we replaced the employment outcomes by the natural logarithm of the hourly real wage at the start of the first job<sup>18</sup>. Unlike for the other outcomes, we do not find that internships affect starting wages. As already argued earlier, this is most likely explained by the strong minimum wage and collective bargaining institutions in Belgium.

< Table 5 about here >

## 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

---

<sup>16</sup> This is the first job with a standard labor contract, which excludes internships, apprenticeships or student jobs.

<sup>17</sup> This information was derived from the occupational code of the first standard job. This coding was based on self-reported information about the occupational title, tasks to be executed and the number of employees to be supervised.

<sup>18</sup> Hourly wages are derived from self-reports on monthly wages and hours of work. Observations with extreme values of wages, being defined as those falling outside two standard deviations from the natural logarithm of the hourly wage, are excluded from the wage analysis. Wages outside these boundaries are beyond what were realistic starting wages at the time of observation; for instance, the lower bound for selecting the sample is equivalent to a net monthly real wage of €749 (prices 2005) and is still clearly below the lowest net minimum wage during the period under consideration (see Cantillon, Marx, and De Maesschalck, 2003).

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 somewhat 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 slightly 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 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 unable to account for the potential confounding role of downgrading after year four in secondary education. While additional robustness checks did not indicate this to be a major issue, further research relying on more detailed information regarding the timing of internships would be welcome.

Third, 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 last 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.

## References

Adda, J., Dustmann, C., Meghir, C., and Robin, J. M. (2010), "Career progression and formal versus on-the-job training", *IFS Working Papers* 10/13.



Arum, R., and Shavit, Y. (1995), "Secondary vocational education and the transition from school to work", *Sociology of Education* 68, 187–204.

Baert, S., and Cockx, B. (2013), "Pure ethnic gaps in educational attainment and school to work transitions. When do they arise? ", *Economics of Education Review* 36, 276–294.

Baert, S., Neyt, B., Siedler, T., Tobback, I., and Verhaest, D. (2021), "Student internships and employment opportunities after graduation: A field experiment", *Economics of Education Review* 83, 102141.

Becker, G. S. (1964), *Human Capital: A Theoretical and Empirical Analysis, with Special Reference to Education*, New York: National Bureau of Economic Research.

Brunello, G., and Rocco, L. (2017), "The labor market effects of academic and vocational education over the life cycle: Evidence based on a British cohort", *Journal of Human Capital* 11, 106–166.

Cameron, S. V., and Heckman, J. J. (1998), "Life cycle schooling and dynamic selection bias: Models and evidence for five cohorts of American males", *Journal of Political Economy* 106, 262–333.

Cameron, S. V., and Heckman, J. J. (2001), "The dynamics of educational attainment for black, Hispanic and white males", *Journal of Political Economy* 109, 455–499.

Cantillon, B., Marx, I., and De Maesschalck, V. (2003). « De bodem van de welvaartsstaat van 1970 tot nu, en daarna", *CSB Berichten No. 03/01*, Antwerp: Centrum voor Sociaal Beleid.

Cockx, B., Picchio, M., and Baert, S. (2019), "Modeling the effects of grade retention in high school", *Journal of Applied Econometrics* 34, 403–424.

Gaure, S., Røed, K., and Zhang, T. (2007), "Time and causality: A Monte Carlo assessment of the timing-of-events approach", *Journal of Econometrics* 141, 1159–1195.

Granovetter, M. S. (1973), "The strength of weak ties", *American Journal of Sociology* 78, 1360–1380.

Gault, J., Redington, J., and Schlager, T. (2000), "Undergraduate business internships and career success: Are they related? ", *Journal of Marketing Education* 22, 45–53.

Hampf, F., and Woessmann, L. (2017), "Vocational vs. general education and employment over the life cycle: New evidence from PIAAC", *CESifo Economic Studies* 63, 255–269.

Hanushek, E. A., Schwerdt, G., Woessmann, L., and Zhang, L. (2017), “General education, vocational education, and labor-market outcomes over the lifecycle”, *Journal of Human Resources* 52, 48–87.

Hotz, V. J., Xu, L. C., Tienda, M., and Ahituv, A. (2002), “Are there returns to the wages of young men from working while in school? ”, *Review of Economics and Statistics* 84, 221–236.

Jaeger, D. A., Nunley, J. M., Seals, A., and Wilbrandt, E. J. (2020). “The Demand for Interns”, *NBER Working Paper Series No. 26729*, Cambridge: National Bureau of Economic Research.

Jørgensen, C. H. (2015), “Some boys’ problems in education – what is the role of VET? ”, *Journal of Vocational Education and Training* 67, 62–77.

Keane, M. P., Todd, P. E., and Wolpin, K. I. (2011), “The structural estimation of behavioral models: Discrete choice dynamic programming methods and applications”, in *Handbook of Labor Economics*, Vol. 4, 331–461, Amsterdam: Elsevier.

Kuczera, M. (2017), “Incentives for apprenticeship”, *OECD Education Working Paper No. 152*.

Lavrijsen, J., and Nicaise, I. (2017), “Returns on vocational education over the life cycle: Between immediate labour market preparation and lifelong employability”, *International Review of Education* 63, 257–280.

Margaryan, S., Saniter, N., Schumann, M., and Siedler, T. (2020), “Do internships pay off? The effects of student internships on earnings”, *Journal of Human Resources*, preprint manuscript. <https://doi.org/10.3368/jhr.57.4.0418-9460R2>.

Neyt, B., Verhaest, D., and Baert, S. (2020), “The impact of dual apprenticeship programs on early labour market outcomes: A dynamic approach”, *Economics of Education Review* 78, No. 102022.

Nunley, J. M., Pugh, A., Romero, N., and Seals, R. A. (2016), “College major, internship experience, and employment opportunities. Estimates from a résumé audit. *Labour Economics* 38, 37–46.

OECD (2013), *The OECD action plan for youth – Giving youth a better start in the labour market*, Paris: OECD Publishing.

OECD (2019a), *Unemployment rate (indicator)*. doi: 10.1787/997c8750-en (Accessed on 10 September 2019).

OECD (2019b), *Youth unemployment rate (indicator)*. doi: 10.1787/c3634df7-en (Accessed on 10 September 2019).

Pilz, M. (2009), “Why Abiturienten do an apprenticeship before going to university: The role of ‘double qualifications’ in Germany”, *Oxford Review of Education* 35, 187–204.

Powell, J. J. W., and Solga, H. (2011), “Why are higher education participation rates in Germany so low? Institutional barriers to higher education expansion”, *Journal of Education and Work*, 24, 49–68.

Spence, M. (1973). “Job Market Signaling”, *Quarterly Journal of Economics* 87, 355–374.

Stiglitz, J. E. (1975), “The theory of “screening,” education, and the distribution of income”, *American Economic Review* 65, 283–300.

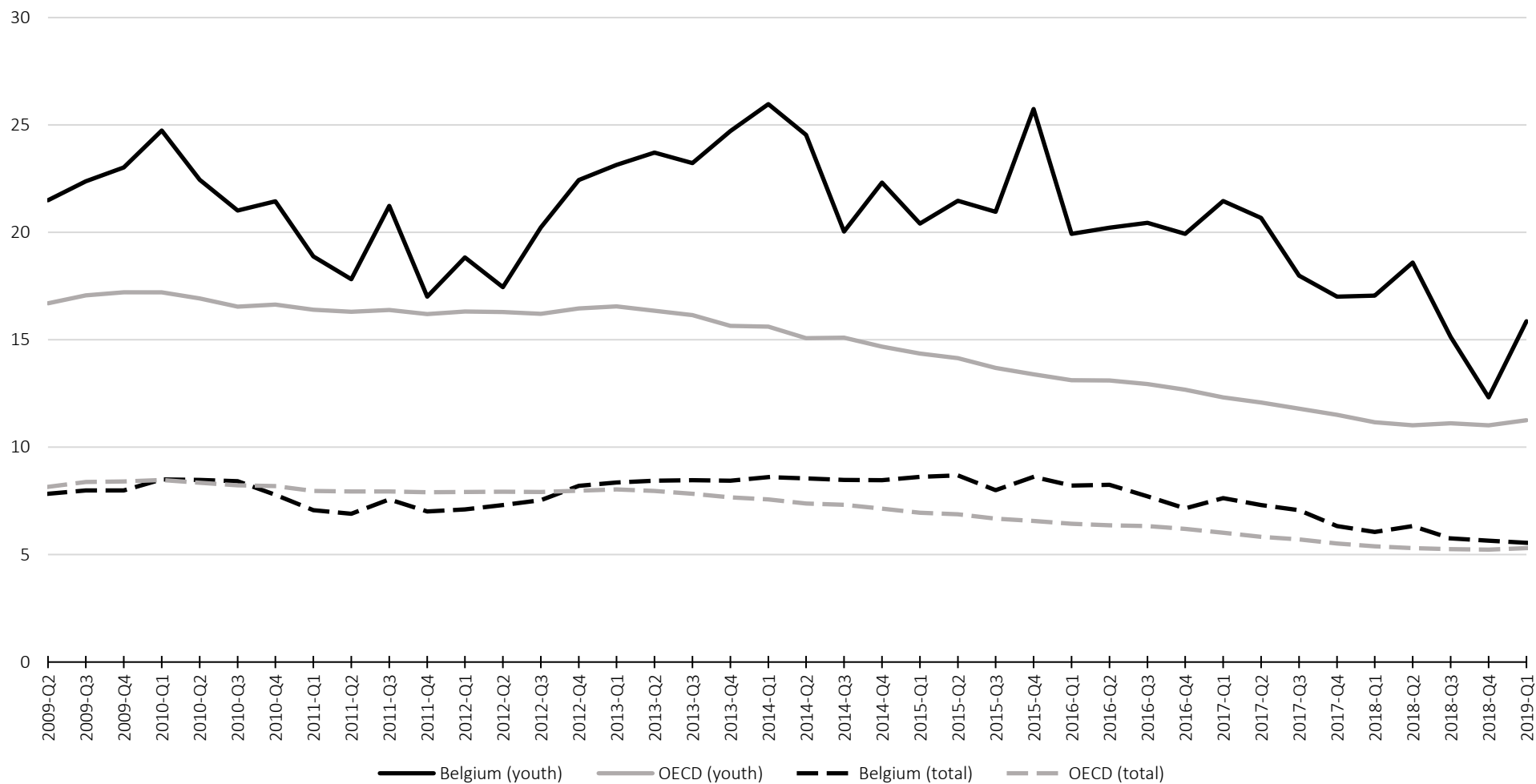
Van Belle, E., Caers, R., Cuypers, L., De Couck, M., Neyt, B., Van Borm, H., and Baert, S. (2019), “What do student jobs on graduate CVs signal to employers? ”, *IZA Discussion Paper Series No. 12431*.

Verhaest, D., Lavrijssen, J., Van Trier, W., Nicaise, I., and Omey, E. (2018), “General education, vocational education and skill mismatches: Short-run versus long-run effects”, *Oxford Economic Papers* 70, 974–993.

Weber, S. (2014), “Human capital depreciation and education level”, *International Journal of Manpower* 35, 613–642.

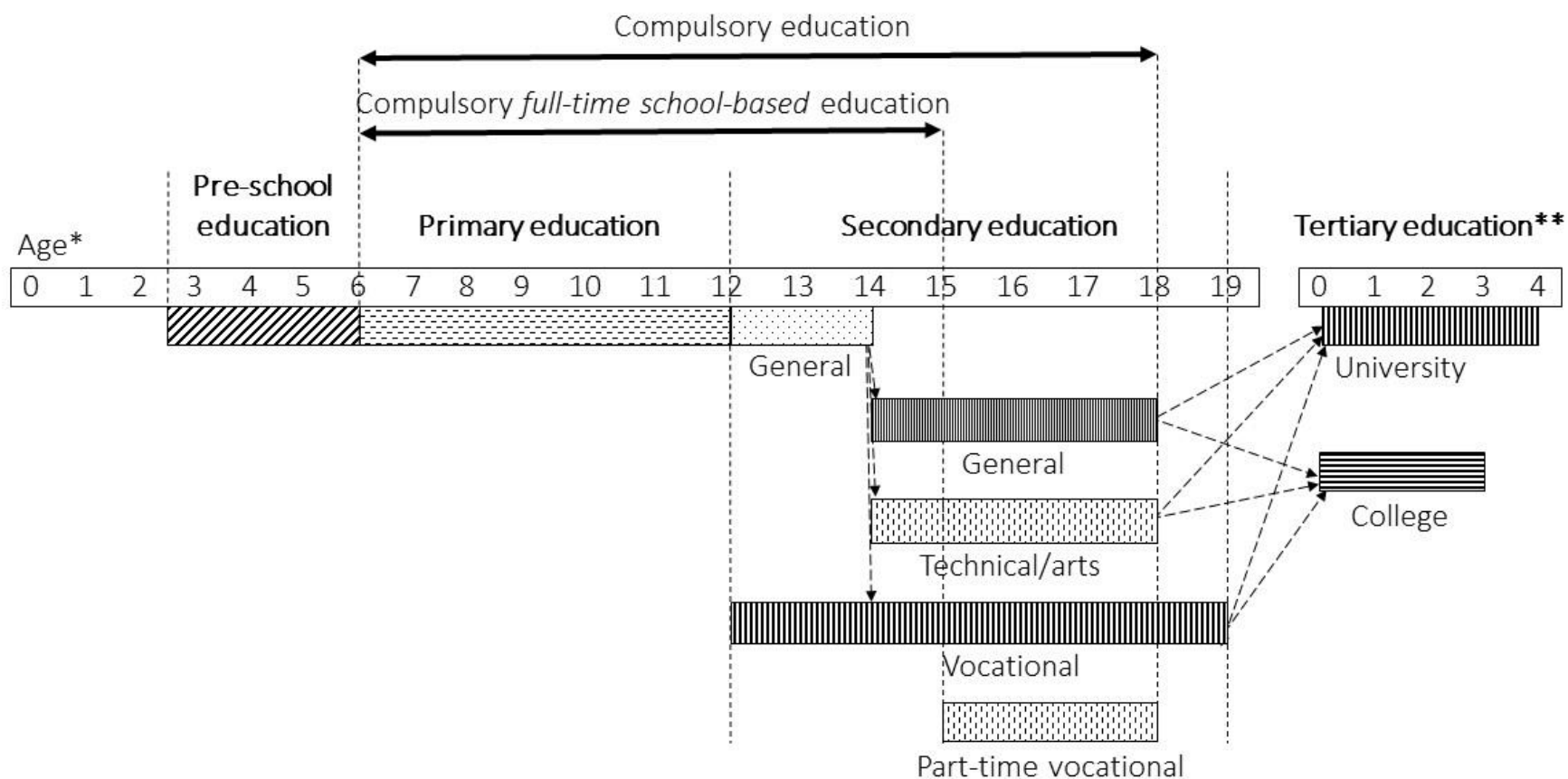
Zilic, I. (2018), “General versus vocational education: Lessons from a quasi-experiment in Croatia”, *Economics of Education Review* 62, 1–11.

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



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

**Figure 2.** Organisation of education in Flanders during the period under consideration.



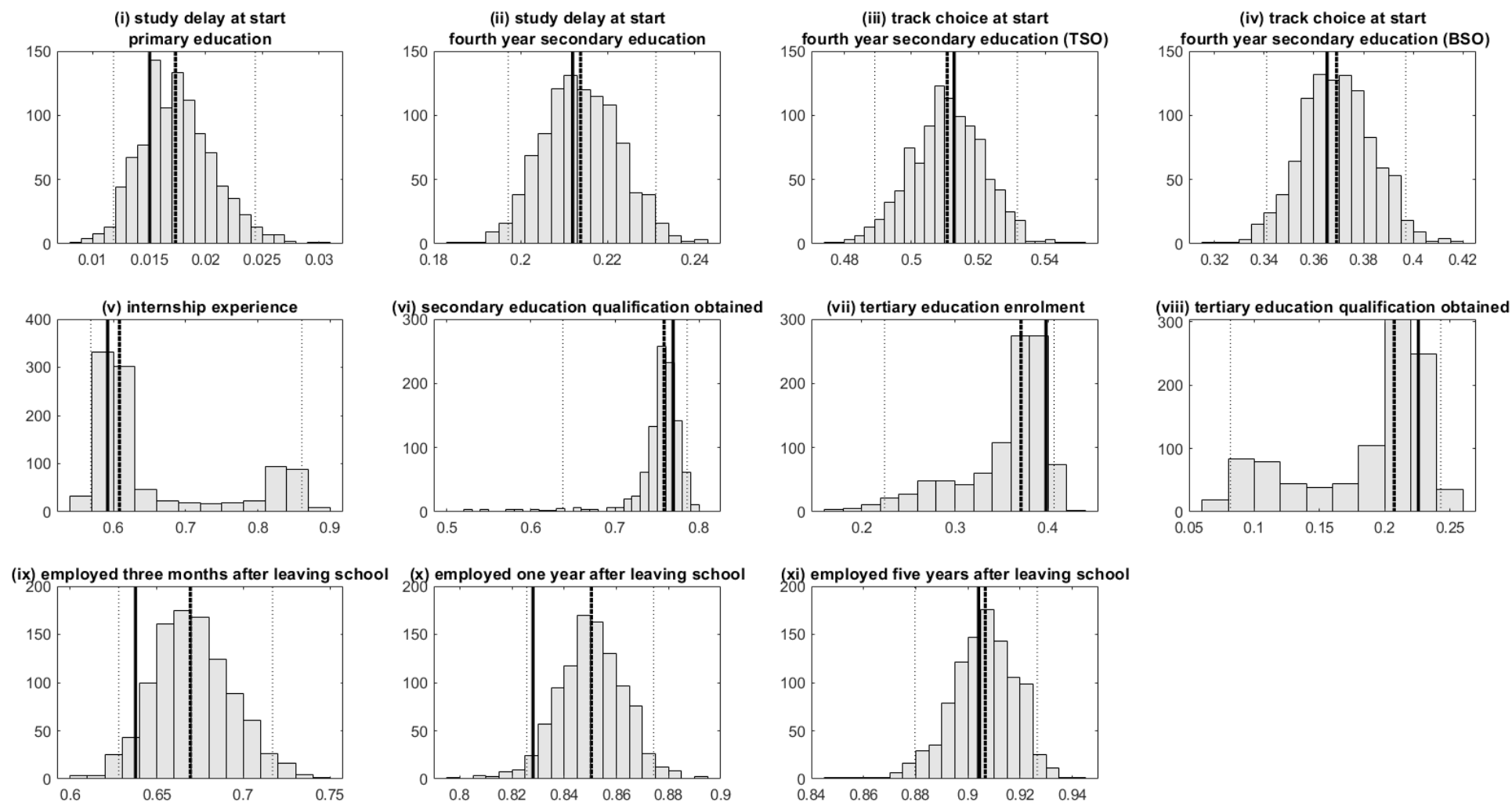
Notes. As the individuals in our sample were born up to 1980, the figure represents the system prior to the Bologna reforms that were implemented in 2014. (\*) In pre-school, primary and secondary education, the timeline indicates the minimum ages to start a programme and to obtain a qualification. (\*\*) In tertiary education, the timeline indicates the minimum programme duration in years.

**Figure 3.** 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 4. 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 (N = 2,408)		II. Sample without internship experience (N = 992)		III. Sample with internship experience (N = 1,416)	
	Mean	SD	Mean	SD	Mean	SD
<b>A. Exogenous variables</b>						
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
Cohort	1.520	0.499	1.511	0.500	1.526	0.499
<b>B. Endogenous variables</b>						
<b>B.1. Variables related to selection into internships</b>						
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>B.2. Variables related to internships</b>						
Internship experience	0.588	0.492	0.000	0.000	1.000	0.000
<b>B.3. Variables related to schooling outcomes</b>						
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>B.4. Variables related to labour market outcomes</b>						
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)
	<b>Total effect</b>		
	<b>Labour market outcome: employed after leaving school</b>		
	<b>No correction for unobserved heterogeneity</b>	<b>Correction for unobserved heterogeneity</b>	
	<b>(K = 1)</b>	<b>(K = 3)</b>	
Secondary education qualification obtained	1.242*** [1.157, 1.335]	1.693*** [1.224, 3.332]	
Tertiary education enrolment	0.597*** [0.526, 0.673]	0.772** [0.518, 0.952]	
Tertiary education qualification obtained	0.765*** [0.652, 0.881]	0.630* [0.232, 1.008]	
Employed three months after leaving school	1.041 [0.956, 1.126]	1.201** [1.028, 1.500]	
Employed one year after leaving school	1.048** [1.001, 1.101]	1.218*** [1.043, 1.542]	
Employed five years after leaving school	1.005 [0.960, 1.049]	1.176** [1.012, 1.568]	

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	1.201** [1.028, 1.500]	1.195** [1.001, 1.552]
Employed one year after leaving school	1.218*** [1.043, 1.542]	1.124** [1.001, 1.382]
Employed five years after leaving school	1.176** [1.012, 1.568]	1.166 [0.982, 1.602]

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 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	1.201** [1.028, 1.500]		1.978*** [1.435, 2.575]
Employed one year after leaving school	1.218*** [1.043, 1.542]		1.371*** [1.123, 1.648]
Employed five years after leaving school	1.176** [1.012, 1.568]		1.197*** [1.061, 1.343]

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 5.** ATEs of internship experience on the quality of the first standard job after graduation.

	(1)		(2)	
	Correction for unobserved heterogeneity (K = 3)			
	Total effect		Total effect	
	At least medium skilled job		Ln (real hourly starting wage)	
Job quality first job	1.472**	[1.023, 2.097]	-0.004	[-0.011, 0.002]

Notes. The presented statistics are simulated Average Treatment Effects and 95% confidence intervals are given between brackets. While the ATE for the “at least medium skilled job” outcome is expressed as a ratio, the ATE with respect to wages is expressed as the absolute change in log points. \* (\*\*) ((\*\*)) indicates significance at the 10% (5%) ((1%)) significance level.

**Table A–1.** Model selection.

(1)	(2)	(3)	(4)
# heterogeneity types (K)	# parameters	Log-likelihood	Akaike Information Criterion
1	143	-12,364.701	25,015.403
2	155	-12,299.028	24,908.055
<b>3</b>	<b>167</b>	-12,274.324	<b>24,882.649</b>
4	179	-12,267.776	24,893.553
5	191	-12,257.017	24,896.034

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).

<b>A. Outcome: study delay at start primary education</b>		
Female gender	-0.077	(0.313)
Migration background	1.257**	(0.519)
Number of siblings	0.069	(0.112)
Mother's education after primary education (years)	0.039	(0.069)
Father's education after primary education (years)	-0.026	(0.063)
Day of birth within calendar year	0.005***	(0.002)
Unemployment rate	0.032	(0.076)
Cohort	0.283	(0.342)
Intercept	-6.210***	(1.492)
<b>B. Outcome: study delay at start fourth year secondary education</b>		
Female gender	-0.636***	(0.084)
Migration background	0.701***	(0.177)
Number of siblings	0.107***	(0.030)
Mother's education after primary education (years)	-0.085***	(0.016)
Father's education after primary education (years)	-0.058***	(0.015)
Day of birth within calendar year	0.002***	(0.000)
Unemployment rate	0.015	(0.014)
Study delay at start primary education	2.939***	(0.442)
Cohort	-0.024	(0.083)
Intercept	-0.450	(0.298)
<b>C. Outcome: track choice at start fourth year secondary education – technical or vocational track</b>		
Female gender	-0.577***	(0.110)
Migration background	-0.653**	(0.287)
Number of siblings	0.045	(0.043)
Mother's education after primary education (years)	-0.232***	(0.028)
Father's education after primary education (years)	-0.239***	(0.025)
Day of birth within calendar year	0.002***	(0.000)
Unemployment rate	0.039**	(0.017)
Study delay at start primary education	1.041	(0.717)
Study delay at start fourth year secondary education	1.509***	(0.205)
Cohort	0.271***	(0.099)
Intercept	2.490***	(0.518)
<b>D. Outcome: track choice at start fourth year secondary education – vocational track</b>		
Female gender	0.281**	(0.121)
Migration background	0.040	(0.278)
Number of siblings	0.158***	(0.048)
Mother's education after primary education (years)	-0.174***	(0.024)
Father's education after primary education (years)	-0.135***	(0.023)
Day of birth within calendar year	0.000	(0.001)
Unemployment rate	0.003	(0.019)
Study delay at start primary education	1.134*	(0.640)
Study delay at start fourth year secondary education	1.085***	(0.147)
Cohort	-0.095	(0.117)
Intercept	-2.202***	(0.604)
<b>E. Outcome: internship experience</b>		
Female gender	0.926***	(0.182)
Migration background	-0.723**	(0.288)

Number of siblings	-0.029	(0.057)
Mother's education after primary education (years)	0.022	(0.034)
Father's education after primary education (years)	0.081***	(0.031)
Day of birth within calendar year	0.001*	(0.001)
Unemployment rate	0.012	(0.027)
Study delay at start primary education	-1.659*	(0.857)
Study delay at start fourth year secondary education	-0.558***	(0.181)
Track choice: vocational track	7.315	(8.640)
Cohort	0.213	(0.166)
Intercept	0.701	(0.577)

#### **F. Outcome: secondary education qualification obtained**

Female gender	0.407**	(0.164)
Migration background	0.072	(0.342)
Number of siblings	-0.012	(0.060)
Mother's education after primary education (years)	-0.034	(0.033)
Father's education after primary education (years)	0.057*	(0.032)
Day of birth within calendar year	0.001	(0.001)
Unemployment rate	-0.013	(0.036)
Study delay at start primary education	2.028**	(0.811)
Study delay at start fourth year secondary education	-0.388**	(0.182)
Track choice: vocational track	-7.635**	(3.260)
Internship experience	3.302***	(0.390)
Cohort	-0.037	(0.188)
Intercept	-1.076	(0.753)

#### **G. Outcome: tertiary education enrolment**

Female gender	1.053***	(0.137)
Migration background	-0.062	(0.306)
Number of siblings	0.050	(0.054)
Mother's education after primary education (years)	0.060**	(0.025)
Father's education after primary education (years)	0.119***	(0.024)
Day of birth within calendar year	0.001**	(0.001)
Unemployment rate	0.062**	(0.028)
Study delay at start primary education	-0.589	(0.787)
Study delay at start fourth year secondary education	-0.201	(0.148)
Track choice: vocational track	-1.730**	(0.728)
Internship experience	-1.627**	(0.710)
Cohort	0.254*	(0.148)
Intercept	-1.183	(0.874)

#### **H. Outcome: tertiary education qualification obtained**

Female gender	0.664***	(0.168)
Migration background	0.103	(0.473)
Number of siblings	0.119**	(0.058)
Mother's education after primary education (years)	0.035	(0.033)
Father's education after primary education (years)	0.077**	(0.030)
Day of birth within calendar year	0.001	(0.001)
Unemployment rate	-0.124**	(0.049)
Study delay at start primary education	-1.109	(1.305)
Study delay at start fourth year secondary education	-0.775***	(0.210)
Track choice: vocational track	0.643	(1.329)

Internship experience	-2.630*	(1.354)
Cohort	-0.099	(0.155)
Intercept	2.363	(1.449)

#### **I. Outcome: employed three months after leaving school**

Female gender	-0.683***	(0.115)
Migration background	-0.613***	(0.219)
Number of siblings	-0.045	(0.040)
Mother's education after primary education (years)	-0.009	(0.021)
Father's education after primary education (years)	-0.059***	(0.020)
Day of birth within calendar year	0.000	(0.000)
Unemployment rate	-0.092***	(0.025)
Study delay at start primary education	0.412	(0.635)
Study delay at start fourth year secondary education	-0.056	(0.117)
Track choice: vocational track	-0.243	(0.318)
Internship experience	0.573**	(0.266)
Secondary education qualification obtained	0.163	(0.222)
Tertiary education enrolment	-0.377**	(0.165)
Tertiary education qualification obtained	1.043***	(0.191)
Cohort	0.135	(0.110)
Intercept	1.350***	(0.448)

#### **J. Outcome: employed one year after leaving school**

Female gender	-0.581***	(0.159)
Migration background	-0.350	(0.288)
Number of siblings	-0.054	(0.054)
Mother's education after primary education (years)	-0.003	(0.030)
Father's education after primary education (years)	-0.042	(0.030)
Day of birth within calendar year	-0.002**	(0.001)
Unemployment rate	-0.144***	(0.035)
Study delay at start primary education	-0.107	(0.703)
Study delay at start fourth year secondary education	0.161	(0.165)
Track choice: vocational track	-0.664	(0.428)
Internship experience	0.666**	(0.331)
Secondary education qualification obtained	0.368	(0.280)
Tertiary education enrolment	-0.386*	(0.232)
Tertiary education qualification obtained	1.368***	(0.288)
Employed three months after leaving school	2.151***	(0.172)
Cohort	0.133	(0.161)
Intercept	1.611***	(0.586)

#### **K. Outcome: employed five years after leaving school**

Female gender	-0.753***	(0.258)
Migration background	-0.695*	(0.389)
Number of siblings	-0.169***	(0.063)
Mother's education after primary education (years)	0.048	(0.044)
Father's education after primary education (years)	-0.047	(0.046)
Day of birth within calendar year	0.002	(0.001)
Unemployment rate	-0.050	(0.068)
Study delay at start primary education	0.346	(1.372)
Study delay at start fourth year secondary education	-0.130	(0.243)
Track choice: vocational track	-1.598*	(0.910)



Internship experience	0.976	(0.667)
Secondary education qualification obtained	-0.128	(0.625)
Tertiary education enrolment	0.043	(0.439)
Tertiary education qualification obtained	1.109	(0.739)
Employed three months after leaving school	0.089	(0.306)
Employed one year after leaving school	1.136***	(0.270)
Cohort	-0.095	(0.238)
Intercept	1.695**	(0.696)
<b>L. Unobserved heterogeneity distribution</b>		
$\eta_2$ : Study delay at start primary education	0.659	(0.559)
$\delta_2^2$ : Study delay at start fourth year secondary education	-1.637***	(0.322)
$\delta_2^3$ : Track choice: technical or vocational track	-4.543***	(0.567)
$\delta_2^4$ : Track choice: vocational track	1.558*	(0.817)
$\delta_2^5$ : Internship experience	-0.927	(0.933)
$\delta_2^6$ : Secondary education qualification obtained	4.388	(3.413)
$\delta_2^7$ : Tertiary education enrolment	2.280*	(1.257)
$\delta_2^8$ : Tertiary education qualification obtained	1.307	(1.207)
$\delta_2^9$ : Employed three months after leaving school	-4.844	(8.391)
$\delta_2^{10}$ : Employed one year after leaving school	0.433	(1.028)
$\delta_2^{11}$ : Employed five years after leaving school	-0.452	(1.582)
$q_2$	-0.184	(0.230)
$\eta_3$ : Study delay at start primary education	-1.571**	(0.740)
$\delta_3^2$ : Study delay at start fourth year secondary education	-0.511***	(0.126)
$\delta_3^3$ : Track choice: technical or vocational track	-0.480	(0.350)
$\delta_3^4$ : Track choice: vocational track	3.068***	(0.533)
$\delta_3^5$ : Internship experience	-7.684	(8.630)
$\delta_3^6$ : Secondary education qualification obtained	6.069*	(3.291)
$\delta_3^7$ : Tertiary education enrolment	-0.157	(0.757)
$\delta_3^8$ : Tertiary education qualification obtained	-1.982	(1.394)
$\delta_3^9$ : Employed three months after leaving school	0.483	(0.319)
$\delta_3^{10}$ : Employed one year after leaving school	0.733*	(0.443)
$\delta_3^{11}$ : Employed five years after leaving school	1.817**	(0.915)
$q_3$	0.718***	(0.114)
N	4,600	
# heterogeneity types (K)	3	
# parameters	167	
Log-likelihood	-12,274.325	
Akaike Information Criterion	24,882.649	

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)	(2)
	Actual probability	Simulated probability [95% CI]
Study delay at start primary education	0.015	0.017 [0.012; 0.025]
Study delay at start fourth year of secondary education	0.206	0.214 [0.197; 0.230]
Track choice at start fourth year secondary education – technical of vocational track	0.493	0.511 [0.489; 0.531]
Track choice at start fourth year secondary education – vocational track	0.365	0.369 [0.342; 0.399]
Internship experience	0.588	0.665 [0.569; 0.860]
Secondary education qualification obtained	0.767	0.750 [0.618; 0.786]
Tertiary education enrolment	0.401	0.349 [0.226; 0.411]
Tertiary education qualification obtained	0.228	0.182 [0.080; 0.241]
Employed three months after leaving school	0.638	0.667 [0.628; 0.718]
Employed one year after leaving school	0.828	0.850 [0.824; 0.873]
Employed five years after leaving school	0.904	0.905 [0.878; 0.925]

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

**Table A–4.** Robustness analyses with respect to track downgrade.

Impact of treatment on ...	(i)		(ii)		(iii)	
	Preferred model		Track downgrade		Vocational track only	
... secondary education graduation	3.327***	(0.389)	-0.112	(0.700)	2.974***	(0.389)
... tertiary education enrolment	-1.767**	(0.712)	-1.597	(1.166)	-1.398	(0.908)
... tertiary education graduation	-3.186**	(1.501)	-1.604***	(0.401)	/	
... employment three months after leaving school	0.617**	(0.278)	0.279	(0.463)	0.684**	(0.275)
... employment one year after leaving school	0.747**	(0.348)	0.999*	(0.602)	0.389	(0.328)
... employment five years after leaving school	1.034	(0.700)	-0.795	(0.621)	0.160	(0.527)

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

**Table A–5.** Robustness analyses – testing for heterogeneous effects by social background

	(i)		(ii)		(iii)		(iii)	
	Social background indicator: father with secondary education qualification		Social background indicator: mother with secondary education qualification		Social background indicator: any parent with secondary education qualification		Social background indicator: any parent with tertiary education qualification	
F. Outcome: secondary education qualification obtained								
Internship experience	-0.852	(0.583)	0.348	(0.317)	-0.010	(0.420)	-0.615	(0.494)
Internship experience x social background	0.282	(0.276)	-0.174	(0.213)	-0.088	(0.211)	0.331	(0.274)
G. Outcome: tertiary education enrolment								
Internship experience	-1.593***	(0.246)	-1.312***	(0.199)	-1.511***	(0.253)	-1.578***	(0.198)
Internship experience x social background	0.106	(0.226)	-0.209	(0.214)	0.039	(0.220)	0.238	(0.217)
H. Outcome: tertiary education qualification obtained								
Internship experience	-0.444	(0.342)	-0.615**	(0.285)	-0.528	(0.383)	-0.658**	(0.264)
Internship experience x social background	-0.311	(0.306)	-0.055	(0.299)	-0.153	(0.341)	0.006	(0.288)
I. Outcome: employed three months after leaving school								
Internship experience	0.099	(0.172)	-0.165	(0.182)	-0.246	(0.194)	-0.031	(0.155)
Internship experience x social background	0.265	(0.162)	0.167	(0.166)	0.209	(0.163)	-0.172	(0.185)
J. Outcome: employed one year after leaving school								
Internship experience	-0.055	(0.389)	0.370	(0.272)	0.144	(0.364)	0.084	(0.322)
Internship experience x social background	0.131	(0.278)	-0.358	(0.251)	-0.062	(0.257)	-0.134	(0.286)
K. Outcome: employed five years after leaving school								
Internship experience	-0.838	(0.586)	-0.350	(0.444)	-0.634	(0.555)	-0.507	(0.546)
Internship experience x social background	0.529	(0.388)	0.377	(0.379)	0.487	(0.369)	0.061	(0.503)

Notes. The presented statistics are estimated coefficients and standard errors between parentheses. Except for the included interaction terms, the model specification is the same as in the benchmark analysis. \* (\*\*) (\*\*\*) indicates significance at the 10% (5%) (1%) significance level.