Educational Attainment, Overeducation and Wages: Evidence from a Dynamic Model

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Abstract

We estimate a Dynamic Discrete Choice Model to investigate the causal relationship between educational attainment, overeducation in the first job after graduation and subsequent wages. Moreover, we introduce a novel decomposition approach to analyze how overeducation risk affects the expected (unconditional) wage returns to educational attainment and their distribution. To this end, we rely on longitudinal Belgian data. We find initial overeducation to generate a wage penalty that persists at least up until age 29. Even so, the effect of overeducation risk on the expected return to college is found to be moderate at best and, in some cases, even positive. This is partly due to a reduced overeducation risk that results from obtaining a bachelor's degree, most likely as a consequence of job polarization. We also find overeducation to generate substantial heterogeneity in realized (ex-post) returns to education. Overall, these results suggest overeducation to be much more indicative of search and matching frictions on the labour market rather than of considerable overinvestments in higher education.

Keywords: Educational Mismatch; Underemployment; Dynamic Discrete Choice Model; Returns to Education; Educational Expansion; Heterogeneous Returns

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1 Introduction

Supported by the overwhelming evidence on both the pecuniary and non-pecuniary returns to education (Oreopoulos and Salvanes, 2011; Heckman et al., 2018a, 2018b; Gunderson and Oreopolous, 2020), most developed countries have realized over the past decades a substantial expansion of the population with a tertiary education degree. However, these benefits may be limited for a significant pool of the graduates that are observed to start their careers in jobs that do not require a college degree (Groot and Maassen van den Brink, 2000; McGuinness, 2006; Verhaest and van der Velden, 2013; McGuinness et al., 2018). Indeed, these initially underemployed or so-called "overeducated" graduates are usually found to earn a lower wage relative to adequately educated graduates that obtained similar degrees (Hartog, 2000; Barnichon and Zylberberg, 2019) and also in terms of the non-pecuniary characteristics of their jobs, these graduates seem to be worse off (Verhaest and Omey, 2009). Finally, several studies also find initial overeducation to be persistent (Baert et al., 2013; Meroni and Vera-Toscano, 2017; Barnichon and Zylberberg, 2019) and to lead to higher chances to become unemployed later on (Sloane et al., 1999; Mavromaras et al., 2013).

Several explanations have been advanced about why part of the graduates are persistently overeducated and, as a result, may fail to fully capitalize on the potential benefits of higher education. One explanation is that overeducation is the result of search and matching frictions (Gautier et al., 2002; Dolado et al., 2009). Although this overeducation is often thought to be temporary, it may persist for several reasons, such as decreased on-the-job search (Holzer, 1987), locking in effects due to job specific human capital investments (Pissarides, 1994), negative signaling effects (McCormick, 1990) or a depreciation of underutilized skills (de Grip et al., 2008). According to this explanation, overeducation thus mainly leads to heterogeneous realised (ex-post) returns to college and generates risk in the schooling decision (Leuven and Oosterbeek, 2011). Another suggested explanation is that overeducation results from heterogeneous skills across graduates. Indeed, many studies found overeducated workers to score lower on ability tests or on their obtained GPA (Green et al., 2002; Agopsowicz et al., 2020), while others suggest part of the workers to be overeducated without being overskilled (Allen and van der Velden, 2001; Chevalier, 2003; Green and McIntosh, 2007). Based on this explanation, overeducation may thus also be a channel that generates the heterogeneity in expected (ex-ante) returns to college as found in several studies that do not focus on overeducation (see, e.g., Arcidiacono, 2004; Rodriguez et al., 2016).

A more controversial, but also quite popular explanation, is that overeducation is the result of more general overinvestments in higher education (McGuinness, 2006; Leuven and Oosterbeek, 2011). Indeed, employers may respond to an expansion of tertiary education by increasing hiring requirements (Thurow, 1975; Charlot et al., 2005). In the longer run, however, labour markets are likely to generate more high-skilled vacancies in response (Gautier, 2002; Dolado et al., 2009; Ordine and Rose, 2017; Di Cintio et al., 2022). Moreover, as argued by Goldin and Katz (2008), technology has been complementary to education for most parts of the past century[1]. And according to the routinisation hypothesis (Autor et al., 2003; Goos et al., 2009), these technological advances have primarily served as substitutes for medium-skilled labour over the past decades and rather led to a polarized labour market. Given this observation, one may thus expect the attainment of a college degree to be just as well an effective way to avoid overeducation. Indeed, a few descriptive studies for the UK and Belgium indicated the chance to be overeducated to be lower for the high than for the medium-skilled (Sloane et al., 1999; Verhaest and Omey, 2006)[2] and also macro-level studies usually failed to find a positive association between the share of highly skilled workers and the overeducation incidence (Verhaest and van der Velden, 2013; McGuinness et al., 2018; Delanay et al., 2020)[3]. However, it is unclear whether these findings can be given a causal interpretation.

In this paper, we contribute to this discussion by investigating whether and how an increase in one's educational attainment affects one's likelihood to be overeducated and one's wage. To this end, we estimate a Dynamic Discrete Choice (DDC) model based on longitudinal data about Belgian young peoples' educational and early labour market careers. In this approach, career decisions are modelled as a sequence of choices that each depends on past decisions as well as on observed and unobserved characteristics (Cameron

[1]Acemoglu (1998) claims that the increase in the number of high-skilled workers itself may have initiated technological advances that are complementary to their own employment.

[2]By looking at a large range of European countries, Lessear et al. (2015) meanwhile found underemployment to be dominant among the medium-skilled workers in a few Southern European countries only. However, as the authors explain, this is likely due to the specific measure of underemployment (i.e. a so-called "realized matches" measure) that was adopted. We turn back to this in the methods section.

[3]This conclusion often changes once also the demand for high-skilled workers is controlled for in the analysis (e.g. Verhaest and van der Velden, 2013; Davia et al. 2017; Charalambidou and McIntosh, 2021). However, as argued, the high-skill job demand is likely to respond endogenously to the change in high-skill supply.

and Heckman, 2001; Carneiro et al., 2003; Heckman and Navarro, 2007; Heckman et al., 2016, 2018a, 2018b). Most of the individuals in our data entered the labour market between 1994 and 2003, a period for which the process of job polarization is well documented (Goos et al., 2009). Also, the Belgian case is interesting, as it combines a higher education system that is characterized by high levels of public subsidization and low tuition fees with compulsory schooling up until age 18. As a consequence, participation in higher education is quite high and few young people enter the labour market without a higher secondary education degree.

Our modelling approach allows us to address three main gaps in the literature on educational participation, overeducation and wages. First of all, it allows us to investigate the relationship between one's educational attainment, overeducation and wages in a causal way. Not only is there a lack of evidence on the causal effect of educational attainment on overeducation, also the question of whether the wage penalty to overeducation presents a causal effect is still open to debate (Leuven and Oosterbeek, 2011). Several strategies have been adopted to tackle endogeneity problems. The first strategy is to include ability-related test scores as controls in the wage equation (Chevalier and Lindley, 2009; Levels et al., 2014). Studies adopting this approach typically find differences in skills to explain only a small part of the penalty to overeducation. However, these test scores are unlikely to capture all unobserved differences that may matter in this context. Secondly, a few studies have relied on propensity score matching (McGuinness, 2008; McGuinness and Sloane, 2011). Also these studies usually conclude overeducation affects wages negatively. However, whether the conditional independence assumption is fulfilled is dubious. A third strategy is to rely on fixed-effects panel data methods (Frenette, 2004; Dolton and Silles, 2008; Korpi and Tåhlin, 2009; Verhaest and Omey, 2012; Mavromaras et al., 2013). Overall, this generates more mixed evidence on the importance of unobserved heterogeneity. Moreover, these estimates may be biased due to endogenous job selection. One last strategy is to rely on instrumental variable regression, as is done by Korpi and Tåhlin (2009). However, as this strategy requires finding valid instruments both for education and overeducation, adopting this method in this context is extremely challenging (Leuven and Oosterbeek, 2011). By exploiting the panel nature of our data and accounting for the sequentiality of choices, we are able to derive an unobserved component and account for these endogeneity problems in an alternative way.

Secondly, by analyzing educational participation, overeducation and wages in one and the same model, we are able to implement a more comprehensive approach to gauge the importance of overeducation in explaining overall wage returns to education. The standard approach in the literature on overeducation and wages, introduced by Duncan and Hoffman (1981), is to replace years of education in the Mincer earnings equation with years of overeducation, years of required education and years of undereducation. As the return to years of overeducation is usually found to be lower than the one of years of required education, it is concluded that overeducation generates a wage penalty (Hartog, 2000; McGuinness, 2006; Leuven and Oosterbeek, 2011). However, these returns to years of overeducation and required education merely present returns conditional on one's match status and, therefore, do not take into account how one's match quality is affected by investing in more education. We present a decomposition approach that attributes a part of the average unconditional wage return to education to a return in the case of perfect matching and another part that is attributed to changes in match quality that may be induced by attaining more education. Further, we show that this change in match quality may stem from both differences in the penalty to overeducation and differences in the likelihood to be overeducated across levels of education.

Thirdly, our modeling also allows us to investigate in more detail whether overeducation is a channel that may generate both heterogeneous expected and heterogeneous realised returns to college. Even if part of the graduates is more likely to be overeducated due to lower levels of skills, this should not imply that their return to college is negligible. Not only does the literature indicate the wage return to college conditional on being overeducated is still positive (Hartog, 2000), there is also some evidence that employers prefer overeducated job seekers (Verhaest et al., 2018). Obtaining a college degree may therefore still have improved their chances to secure a medium-skilled job. By conditioning on both observable and unobservables characteristics in our model, we are able to investigate how differences in overeducation probabilities affect the full distribution of expected returns to college. Moreover, by simulating the matching process conditional on the estimated parameters of the model, we are also able to investigate how this matching affects the distribution of realised (ex-post) returns.

In line with the literature, we find initial overeducation to generate a persistent wage penalty. For instance, at age 23, this penalty is estimated to range from about 3%

among those with a high school or bachelor's degree to about 11% among those with a master's degree. However, the effect of overeducation risk on the expected return to college is found to be moderate at best with respect to obtaining a master's degree and even positive with respect to obtaining a bachelor's degree. This is partly due to an associated reduction in overeducation risk and in line with job polarization. Further, although we find differences in overeducation probabilities to reflect differences in expected (unconditional) wage returns across individuals, our results do not suggest overeducation risk in itself to reinforce this heterogeneity. However, we do find overeducation risk to generate substantial heterogeneity in realized (ex-post) returns to education. Overall, these results are much more consistent with overeducation being indicative of search and matching frictions rather than of considerable overinvestments in higher education.

The remainder of our paper is structured as follows. Section 2 introduces our decomposition approach to analyse the role of overeducation risk in explaining the expected unconditional return to education. In Section 3, we describe the institutional setting of Flanders, the northern Dutch-speaking region of Belgium. Section 4 introduces the dataset and the measurement of our key variables. In Section 5, we set up our Dynamic Discrete Choice Model. In Section 6, we present the counterfactual simulation and the relative results of the treatment effects and the heterogeneous treatment effects. Finally, in Section 7, we discuss these results and conclude our paper.

2 Conceptual framework

In this section, we develop a conceptual framework to show how overeducation may both affect the average unconditional wage return to education and generate heterogeneous unconditional wage returns among individuals with the same level of educational attainment. This unconditional wage return ($\Omega_{a,i,j}$) to educational attainment j for individual i, measured at age a, can be defined as:

$$\Omega_{a,i,j} = \mathbb{E}\left[Y_{a,i}^{Wage}|d_j = 1\right] - \mathbb{E}\left[Y_{a,i}^{Wage}|d_{j-1} = 1\right] \quad (1)$$

where d_j (d_{j-1}) indicates having obtaining level of educational attainment j ($j-1$), and $\mathbb{E}\left[Y_a^{Wage}\right]$ is the expected wage at age a. This unconditional return is thus simply the difference between the expected wage given his or her obtained educational attainment

j and the expected wage when the individual's educational attainment would have been $j-1$ only.

Rather than focusing on this unconditional return, the overeducation literature typically looks at the wage return conditional on one's match status. Depending on the overeducation status of individual i at educational level j, $Y_{i,j}^{OE}$, and one's status at the preceding level $Y_{i,j-1}^{OE}$, we can define the following four conditional wage returns:

$$\Omega_{a,i,j}^{M,M} = \mathbb{E}\left[Y_{a,i}^{Wage}|d_j = 1, Y_{i,j}^{OE} = 0\right] - \mathbb{E}\left[Y_{a,i}^{Wage}|d_{j-1} = 1, Y_{i,j-1}^{OE} = 0\right] \tag{2}$$

$$\Omega_{a,i,j}^{M,O} = \mathbb{E}\left[Y_{a,i}^{Wage}|d_j = 1, Y_{i,j}^{OE} = 1\right] - \mathbb{E}\left[Y_{a,i}^{Wage}|d_{j-1} = 1, Y_{i,j-1}^{OE} = 0\right] \tag{3}$$

$$\Omega_{a,i,j}^{O,M} = \mathbb{E}\left[Y_{a,i}^{Wage}|d_j = 1, Y_{i,j}^{OE} = 0\right] - \mathbb{E}\left[Y_{a,i}^{Wage}|d_{j-1} = 1, Y_{i,j-1}^{OE} = 1\right] \tag{4}$$

$$\Omega_{a,i,j}^{O,O} = \mathbb{E}\left[Y_{a,i}^{Wage}|d_j = 1, Y_{i,j}^{OE} = 1\right] - \mathbb{E}\left[Y_{a,i}^{Wage}|d_{j-1} = 1, Y_{i,j-1}^{OE} = 1\right] \tag{5}$$

where $\mathbb{E}\left[Y_{a,i}^{Wage}|d_j = 1, Y_{i,j}^{OE} = 0, 1\right]$ is expected wage at educational level j when the individual i is either overeducated ($Y_{i,j}^{OE} = 1$) or adequatedly matched ($Y_{i,j}^{OE} = 0$).

While equation (2) describes the return to education presuming one would be adequately matched whatever one's level of educational attainment ($\Omega_{a,i,j}^{M,M}$), equation (3) reflects the return to education when obtaining more education would induce one's match status to switch from an adequate match to overeducation ($\Omega_{a,i,j}^{M,O}$). These two types of conditional returns are equivalent to the two types of returns that are usually reported in the literature on overeducation: the return to (years of) required education and the return to (years of) overeducation respectively. Moreover, by subtracting the return to required education from the return to overeducation, we obtain the so-called wage penalty to overeducation that is frequently reported in the literature as well:

$$\psi_{a,i,j} = \Omega_{a,i,j}^{M,O} - \Omega_{a,i,j}^{M,M} = \mathbb{E}[Y^{Wage}|d_j = 1, Y_{i,j}^{OE} = 1] - \mathbb{E}[Y^{Wage}|d_j = 1, Y_{i,j}^{OE} = 0] \tag{6}$$

As shown in equation (6), this wage penalty of overeducation for educational attainment j is also equal to the difference in the expected wage while being overeducated and the expected wage while being adequately matched for educational attainment j.

The statistic of the wage penalty to overeducation is, along with the proportion of overeducated individuals, often used to gauge the importance of overeducation in reducing the wage return to education. However, also without having obtained more education, some may have been overeducated while others may even manage to improve their match status by obtaining more education. Henceforth, conditional returns $\Omega^{O,O}_{a,i,j}$ and $\Omega^{O,M}_{a,i,j}$ have to be weighted in as well when assessing the importance of overeducation in explaining unconditional returns to education.

To assess more explicitly how important overeducation is in explaining the unconditional return, we implement a decomposition approach to this return. To this end, we first rewrite the expected wage at level of educational attainment j as a weighted average of the conditional wage when being adequately matched and the conditional wage when overeducated:

$$\begin{aligned}\mathbb{E}\left[Y^{Wage}_{a,i}|d_j = 1\right] = (1 - P^{OE}_{i,j})\,\mathbb{E}\left[Y^{Wage}_{a,i}|d_j = 1, Y^{OE}_{i,j} = 0\right] + \\ P^{OE}_{i,j}\,\mathbb{E}\left[Y^{Wage}_{a,i}|d_j = 1, Y^{OE}_{i,j} = 1\right]\end{aligned} \tag{7}$$

where $P^{OE}_{i,j}$ is the probability of being overeducated when having obtained level of educational attainment j. Moreover, by using equation (6), we can rewrite equation (7) in the following way:

$$\mathbb{E}\left[Y^{Wage}_{a,i}|d_j = 1\right] = \mathbb{E}\left[Y^{Wage}_{a,i}|d_j = 1, Y^{OE}_{i,j} = 0\right] + P^{OE}_{i,j}\psi_{a,i,j} \tag{8}$$

Further, by adopting the same logic for the expected wage at level of educational attainment $j-1$, and by using equations (1) and (2), we obtain the following alternative formula for the unconditional wage return:

$$\Omega_{a,i,j} = \Omega^{M,M}_{a,i,j} + P^{OE}_{i,j}\psi_{a,i,j} - P^{OE}_{i,j-1}\psi_{a,i,j-1} \tag{9}$$

At last, by adding and subtracting again the term $P^{OE}_{i,j-1}\psi_{a,i,j}$ to the right-hand side of equation (9), we can decompose the unconditional wage return to education in the following three subcomponents:

$$\Omega_{a,i,j} = \underbrace{\Omega^{M,M}_{a,i,j}}_{\text{(A)}} + \underbrace{P^{OE}_{i,j-1}(\psi_{a,i,j} - \psi_{a,i,j-1})}_{\text{(B)}} + \underbrace{(P^{OE}_{i,j} - P^{OE}_{i,j-1})\psi_{a,i,j}}_{\text{(C)}} \tag{10}$$

where (A) represents the return that may be realised in case of perfect matching, (B) is a subcomponent that is attributed to the potential difference in overeducation penalty between educational attainment j and $j-1$, and (C) is a subcomponent that is attributed to the potential difference in overeducation risk between these two levels of attainment.

Interestingly, the unconditional return collapses to component (A) in the case when the expected match quality is identical across all levels of education. The sum of subcomponents (B) and (C) in equation (10), meanwhile, measures the contribution of any change in expected match quality that may be induced by investing in a higher level of education. Moreover, as overeducation does not affect the unconditional wage return in any other way than through (B+C), this sum thus also serves as a reasonable measure on the importance of overeducation in explaining the unconditional return to education. And given that this component is merely driven by the difference in overeducation penalties and overeducation probabilities across levels of educational attainment, it shows that a focus on absolute overeducation penalties and probabilities may lead to misleading interferences about the importance of overeducation in this respect.

3 Institutional setting

For the estimation of our dynamic discrete choice model and the application of our decomposition approach, we rely on data of the educational and early labour market careers of young individuals in Flanders, the Northern Dutch-speaking region of Belgium. In Flanders, compulsory education starts from September 1st of the year in which the child turns 6 until their 18^{th} birthday or until June 30^{th} of the year in which the child turns 18. Primary education usually starts at the age of 6 and consists of 6 consecutive grades. Subsequently, at the age of 12 in case of no delay, pupils enter secondary education. Secondary education consists of four tracks, namely the general track, the technical track, the art track, and the vocational track, with the technical or art tracks being introduced from grade 9 (i.e. the 3rd grade in secondary education) onward. Between the subsequent grades, students may downgrade from the general to the technical or art tracks, or from the technical or art tracks to the vocational track. From age 15 onwards, students may also opt for a part-time vocational track that may be combined with three to four days of apprenticeship training in a firm. After passing 6 grades in the general, technical or art tracks, or 7 grades in the (full-time) vocational track, individuals may enter tertiary education without any entrance exam (except for medicine) or other entry barriers.

In the period before the Bologna reform, which is the period that is relevant for our sample, individuals could choose in tertiary education between (i) a short-term at a vocationally-oriented college (called "hogeschool" in Dutch), (ii) a long-term program at such a college, or (iii) a more academically-oriented long-term program at a university. While these short-term programs lasted three years, the long-term programs lasted four years or more. Moreover, the long-term programs were subdivided in two stages with the first stage taking two or three years and leading to a so-called "candidate" degree, although it was quite uncommon to leave tertiary education among those who managed to pass this stage. Since the Bologna reform, students have to opt for a so-called professional bachelor degrees at a vocationally-oriented college and an academic bachelor degree at a university, with the latter providing direct access to an academic master degree. Moreover, students may also start in an academic master program program after having obtained a professional bachelor degree conditional on participating first in a one-year bridging program that usually takes one year. Both types of bachelor programs last three years, while the length of master programs is at least one year. By law, the old short-term and long-term degrees have been declared to be equivalent to these new bachelor and master degrees.

4 Data

4.1 Sample

Our model is estimated using the SONAR data. These data include representative samples of three cohorts (birth years 1976, 1978 and 1980) of about 3000 individuals in Flanders that were surveyed for the first time when they were 23 years old. Moreover, these original surveys were supplemented with a number of follow-up surveys, completed at age 26 for the 1976 and 1978 cohorts and at age 29 for the 1976 and 1980 cohorts (the response rates are between 60% and 70%). The data include detailed information regarding schooling and labour market outcomes, among other things by recording each educational choice from age of 6 onwards, and registering core information on one's labour market history on a monthly basis. In addition, the dataset includes a large set of indicators related to the family background as well as information on one's overeducation status and wages both measured at the start of the first job as well as at the moment of the various surveys (ages 23, 26 and 29). To keep the estimated model tractable, we remove from the initial sample those individuals (i) with more than one year of delay at the start of primary education (76 individuals) and (ii) with special needs in schools providing special care (124 individuals). Moreover, we remove another 638 individuals with (iii) inconsistent, erroneous or incomplete data on the exogenous variables (cf. infra) and the educational career. This results in a final sample of 8162 individuals that is used to estimate the equations related to the educational outcomes.

4.2 Exogenous variables

At each stage of our model, we control for the following exogenous background characteristics of the individual: gender (one dummy), foreign origin (one dummy), years of education of the mother and the father (beyond the phase of primary education), number of siblings, year of birth, and day of birth within the calendar year. Most of these variables are standard background characteristics that are usually also included in dynamic discrete choice models on educational careers (e.g. Cameron and Heckman, 2001; Belzil and Poinas, 2010; Heckman et al., 2016, 2018a, 2018b; Baert et al., 2022). In addition, we control for the unemployment rate at the district level to account for differences in labour market conditions. This is a time-varying variable that is measured at the moment of each outcome. Table 2 includes descriptive statistics on each of these exogenous variables.

4.3 Educational attainment and track choices

Our dynamic model, which is outlined in more detail in section 4, includes in total 17 sequential outcomes related to the educational and early labour market career of the individuals. With respect to the educational career, these outcomes include the delay at the start of primary and secondary education along with the enrolment, track choice and attainment related to the following four critical stages in secondary and tertiary education: (i) Lower secondary education, (ii) higher secondary education, (iii) lower tertiary education, and (iv) higher tertiary education. These four stages, along with their acronyms and relation to the ISCED classification, are summarized in Table 1.

We define individuals to have attained lower secondary education (LSE) if they have completed at least the third grade of secondary education, while higher secondary Educa-

Table 1: Codification of educational attainment

Code name	Description	ISCED Code
-	Less than lower secondary education	ISCED 0 and 1
LSE	Lower Secondary Education	ISCED 2
HSE	Higher Secondary Education	ISCED 3 and 4
LTE	Lower Tertiary Education	ISCED 5 - Bachelor
HTE	Higher Tertiary Education	ISCED 5 - Master

tion (HSE) attainment is defined as having completed six grades of secondary education. Regarding tertiary education, lower tertiary education (LTE) attainment is defined as the level of individuals who obtained a short-term college degree or completed, at least, the 3rd grade of a long-term College or University degree. Although in the pre-Bologna system, many long-term programs awarded a candidate qualification after two grades already, these qualifications are usually not considered to be equivalent with a bachelor's degree. By setting the bar at passing at least three grades at university, we follow the logic of the current system to obtain a bachelor's degree at university. Finally, those that have fully completed their long-term college or university degree (i.e. after four or more grades of tertiary education) are defined as having attained higher tertiary education (HTE). The latter level of educational attainment is equivalent with a master degree in the current system.

Enrolment in these four stages is defined as having enrolled in the third grade of secondary education (enrolment LSE), the fifth grade of secondary education (enrolment HSE), the first grade of tertiary education (enrolment LTE) and the fourth grade of tertiary education (enrolment HTE) respectively. Strictly speaking, individuals already enrol in lower secondary education from the first grade of secondary education onward. However, as this is the case for (almost) all individuals in our dataset, we adjust the definition towards enrolment in the third grade. The track choice refers to the (first) year of enrollment in each stage and distinguishes between the general track (in secondary education) or academic track (in tertiary education) and other tracks. The academic track in tertiary education is defined to include all programs at university, while the non-academic track includes programs at (more vocationally-oriented) colleges.

Table 2 (Column (1)) includes the descriptive statistics related to each of these outcomes. Almost all individuals enrol in (99.1 percent) and attain (95.8 percent) a lower

Table 2: Descriptive statistics

	(1) Full Sample		(2) Sample labour market outcomes		(3) Adequately matched first job		(4) Overeducated first job	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
A. *Exogenous variables*:								
Female	0.494	0.500			0.507	0.500	0.475	0.499
Foreign origin	0.056	0.231			0.051	0.220	0.057	0.232
Education Mother	5.738	3.437			5.729	3.408	5.362	3.353
Education Father	6.217	3.675			6.247	3.607	5.625	3.552
Number of siblings	1.669	1.422			1.663	1.377	1.662	1.506
Cohort 1978	0.338	0.473			0.329	0.470	0.338	0.473
Cohort 1980	0.345	0.475			0.325	0.468	0.373	0.484
Birthday date/100	1.718	1.002			1.711	0.999	1.731	1.019
B. *Endogenous variables*:								
B.1. Schooling outcomes								
Delay Primary School	0.015	0.123			0.014	0.118	0.015	0.122
Delay Secondary School	0.101	0.302			0.102	0.302	0.108	0.310
Lower secondary education: enrolment	0.991	0.095			0.987	0.114	0.997	0.056
Lower secondary education: general track	0.524	0.499			0.530	0.499	0.440	0.496
Lower secondary education: qualification obtained	0.954	0.209			0.931	0.253	0.987	0.113
Higher secondary education: enrolment	0.938	0.242			0.912	0.283	0.972	0.164
Higher secondary education: general track	0.442	0.497			0.445	0.497	0.353	0.478
Higher secondary education: qualification obtained	0.887	0.317			0.847	0.360	0.944	0.230
Lower tertiary education: enrolment	0.639	0.480			0.645	0.479	0.561	0.496
Lower tertiary education: academic track	0.214	0.410			0.205	0.404	0.151	0.358
Lower tertiary education: qualification obtained	0.486	0.500			0.527	0.499	0.346	0.476
Higher tertiary education: enrolment	0.215	0.411			0.200	0.400	0.165	0.371
Higher tertiary education: academic track	0.146	0.353			0.140	0.347	0.097	0.296
Higher tertiary education: qualification obtained	0.194	0.395			0.195	0.396	0.162	0.368
B.2. Labour market outcomes								
Overeducation first job			0.351	0.477	0.000	0.000	1.000	0.000
Wage selection at age 23			0.580	0.492	0.561	0.496	0.626	0.484
Log-Hourly Wage at age 23			7.342	1.590	7.445	1.572	7.176	1.606
Wage selection at age 26			0.450	0.497	0.476	0.499	0.403	0.491
Log-Hourly Wage at age 26			8.113	1.866	8.210	1.850	7.909	1.887
Wage selection at age 29			0.423	0.494	0.434	0.496	0.405	0.491
Log-Hourly Wage at age 29			8.546	1.829	8.670	1.843	8.306	1.782
Observations	8162		7211		4648		2563	

secondary education. With respect to higher secondary education this slightly drops to 93.8 and 88.7 percent respectively. When transiting to lower tertiary education, the drop is more substantial, with an enrolment rate of 63.9 percent and an attainment rate of 48.6 percent. Finally, 21.5 and 19.4 percent of the overall sample enrols in and attains a higher tertiary education. Only a small minority of the sample (11.3 percent) can thus be categorized as low-skilled (i.e. less than HS), while the medium- (HS degree) and high-skilled (at least a LT degree) represent 42.1 and 48.6 percent of the sample respectively (see also Table 3). Regarding the track choice, the general or academic track is relatively more frequently chosen at the LSE and HTE stages, while the other (more vocational) tracks are more dominant at the HSE and LTE stages.

Table 3: Educational attainemnt in SONAR data

	Freq.	Percent	Cum.
ISCED 0 or 1	375	4.59	4.59
LSE	551	6.75	11.35
HSE	3,266	40.01	51.36
LTE	2,390	29.28	80.64
HTE	1,580	19.36	100
Total	8,162	100	

4.4 Overeducation

The main outcome of interest in our model is overeducation, which is defined as having attained a level of education that is above the level of education that is required to do one's job well. We focus on the overeducation status at the start of the first job with a standard labour contract, which excludes internships, apprenticeships or student work. For the estimation of the equation related to the overeducation status in the first jobs, the sample is further reduced to 7211 individuals. This is due to 701 individuals for which we have no observation on a first job (either because they did not participate in the follow-up survey(s) or because they didn't have a first job by age 29) and another 250 for which the information on overeducation is missing (see Appendix A).

To measure overeducation, the literature has adopted a wide range of methods that can be subdivided into four broad categories (McGuinness, 2006; Verhaest and Omey, 2006; Leuven and Oosterbeek, 2011): (i) job analysis, (ii) direct self-assessment, (iii) indirect self-assessment, and (iv) realized matches methods. Job analysis methods are usually based on occupational classifications that define the required level of education based on the assessment of job experts. Self-assessment methods, meanwhile, rely on the assessment of the worker itself, either by asking directly whether he or she is overeducated or indirectly by querying about the required level of education to do their job or to be hired for their job. Finally, realized matches methods rather measure the required level of education by the average or modal level of education within one's occupation.

Each of these methods has a number of disadvantages. Job analysis and realized matches methods, for instance, may insufficiently account for the heterogeneity of requirements within categories of jobs with the same occupational title. Moreover, while the job analysis method requires a frequent update of the requirements to account for technological changes, job requirements measured by realized matches methods may be largely endogenous to the composition of the labour force in terms of their educational attainment. Finally, self assessment measures are likely to be prone to all sorts of cognitive biases. For instance, due to lack of expertise in this respect, individuals may find it difficult to gauge the true requirement of their job. Moreover, even if they manage to gauge these requirements correctly, they may be tend to answer in a socially desirable way and inflate their own status.

As our data allow to measure overeducation based on these various methods, we are able to circumvent these problems at least partly. In particular, we assess individuals to be overeducated if they are classified as such based on at least two out of three deliberately chosen measures. The first measure adopts a job analysis approach. In our data, jobs have been coded based on the Standard Occupation Classification of Statistics Netherlands[4]. The classification groups jobs based on five functional levels, where each level represents one of the five considered levels of education in our model (cf. Table 1) that a worker ideally has to properly perform the tasks in the job. A comparison of these job requirements with one's level of attained education therefore allows to derive one's overeducation status based on this method. As shown in Table 4, using only this information, 52% of individuals are considered to be overeducated on the first job.

We complement this job analysis approach with information from one direct and an-

[4]Link to the dataset: Dutch Standard Classification of Occupations (SBC) 1992 (Last accessed: 15.02.2023)

other more indirect (but modified) self-assessment measure. The direct self-assessment measure is derived from the following survey question: "According to your own opinion, do you have a level of education that is too high, too low or appropriate for your job?". 21,5% of the individuals are considered to be overeducated in the first job when using this measure (Table 4). The indirect self-assessment measure is constructed based on the following survey question: "What is (was), according to your own opinion, the most appropriate educational level to execute your first job?". As this question was not included in the survey of the 1976 cohort, we implement a modified procedure following Baert, Cockx and Verhaest (2013)[5]. First, we calculate the median self-assessed required level within each occupation based on the available information. To this end, we rely on the aforementioned five categories of levels of education levels (cf. Table 1). Second, we extrapolate this median to all jobs in each occupation. Third, we assess someone to be overeducated if one's attained level of education exceeds this median required level within one's occupation. Using this procedure, 35,2% of the individuals are overeducated in the first job.

Our choice to combine information on these three measures is based on three main arguments. First of all, we consider these measures to be the ones that are most closely connected with the concept of overeducation as defined in the literature. As hiring requirements may deviate from what is truly needed to do a job, this is less the case for self-assessment measures based on what is required to get the job or realised matches measures that mimic actual hiring behaviour. Second, given our focus on educational attainment and overeducation, we avoid including measures that are endogenous to the educational composition of the workforce. Third, these three measures result from three quite independent assessments. While our first measure relies on the assessment of job experts and the second one is based on the assessment of the worker itself, our third measure can be interpreted as reflecting rather the opinion of the co-workers within one's occupation. Hence, errors that are systematic across two or three of these measures are expected to be limited, while defining someone to be overeducated if classified as such based on two out of three of these assessments should go a long way to account for other, non-systematic errors.

Based on the combination of these three measures, we find 35.5% of the sample to be

[5] More detail on the procedure on this paper.

overeducated for the first job. In line with the idea that overeducated workers are a non-random sample of the population, we find them to be more often male and their parents to be somewhat lower educated (Table 2 (Panel (B)). Moreover, in line with polarisation, we find them to be more likely to have obtained at least a higher secondary education degree and less likely to have obtained also a lower or higher tertiary education degree (Table 2 (Panel (C)).

Table 4: Different measures of overeducation

Variable	Mean	SD
JA	0.520	0.499
DSA	0.215	0.411
ISA	0.352	0.478
BM	0.355	0.479

Notes: The overeducation measures are: Job Analysis (JA), Direct Self-Assessment (DSA), Indirect Self-Assessment (ISA) and Benchmark Measure (BM).

4.5 Wages

To maintain the sequentiality of our model, which is an important precondition to identify causal effects in dynamic discrete choice models, we analyse the wages at age 23, 26 and 29 rather than those at the start of the first job. As a consequence, the estimated wage effects of overeducation in our model are to be interpreted as reduced form effects that result, among other things, from its effect on one's later mismatch status. As shown by Baert et al. (2013) based on a subsample of the same SONAR data, overeducation is strongly persistent. Thus, if overeducation has a contemporaneous effect on wages as is usually found in the literature, we can expect it to affect future wages as well. Moreover, this would also be consistent with a few studies on other countries that found overeducated workers to experience no more wage growth than other workers (Büchel and Mertens, 2004; Korpi and Tåhlin, 2009)[6].

[6] But see Rubb (2006) or Roller et al. (2020) for contrasting findings.

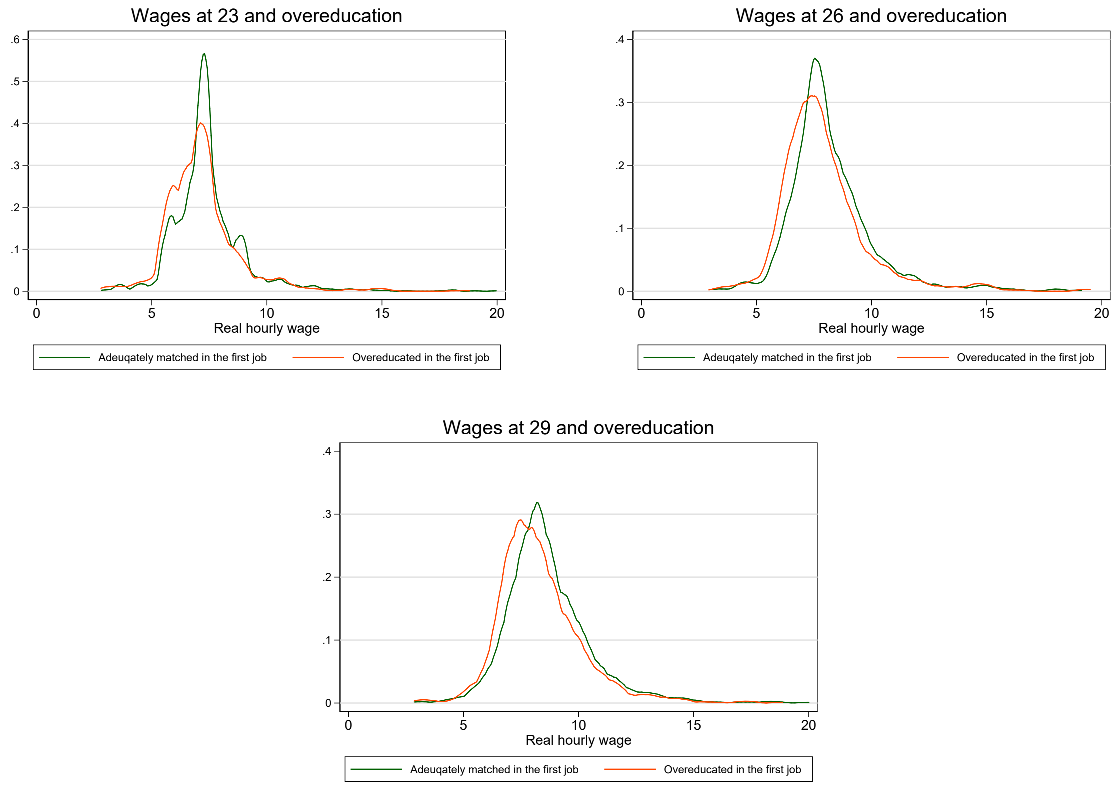
Respondents reported their official net monthly wage. While this was reported in intervals in the first survey of the first cohort, exact wages were reported in later surveys (if respondents refused to answer, they still had the option to report in intervals). For our analysis, we transform these reports to log real hourly net wages (we rely on the midpoint for the interval reports). Due to missing data, the number of observations in the wage equations drops to 4407, 3379, and 3142 with respect to age 23, 26 and 29 respectively. With respect to age 23, this is mainly due to two reasons. First, a significant proportion of the individuals were still in education or without jobs at this age. Second, even if employed, not all individuals were queried about their wage at age 23. In particular, for the 1980 and 1980 cohorts, those who were still in a first job that started less than one year earlier were precluded from answering these questions, while for the 1976 cohort, none of the individuals that were still in their first job (irrespective of when it started) were asked to indicate their wage. With respect to age 26 and age 29, meanwhile, missings on wages are mainly due to a lack of surveying (for the 1978 cohort at age of 26, for the 1980 cohort at age 29) or due to attrition. Missings due to respondents' refusal to answer or to wage outliers are less important for each of the three points of measurement. As these missings are unlikely to be random, we account for this in our analysis by adding three selection equations to our model (cf. infra).

Figure 1 shows the wage distribution at each age depending on the match status in the first job. In line with initial overeducation having a persistent effect on wages, the wage distribution of the overeducated workers is each time positioned to the left of the wage distribution of adequately matched individuals. Based on our model, we will assess whether this difference truly reflects a causal effect of overeducation.

5 Econometric strategy

In this section, we present a dynamic multistage model of educational choices and labour market outcomes. This is used to identify the impact of educational attainment on overeducation and its consequences on future wages, by controlling for dynamic selection and unobserved heterogeneity.

Figure 1: Distribution of wages by overeducation status



5.1 Dynamic discrete choice model

We adopt a dynamic treatment effects aproach[7] (Heckman and Navarro, 2007; Heckman et al., 2016), following the seminal papers of Cameron and Heckman (1998, 2001) and being applied and refined by, among others, Colding (2006), Belzil and Poinas (2010), Adda et al. (2010), Baert and Cockx (2013), Baert, Neyt, Omey, and Verhaest (2017), De Groote (2018), Declercq and Verboven (2018), Heckman et al. (2018a, 2018b), Cockx et al. (2019) and Neyt, Verhaest, Navarini et al. (2022). These dynamic models are characterized by a sequential structure of binary and ordered logit functions, with each choice opening up the possibility of performing particular future choices. This sequential structure is consistent with the organisation of the educational system, whereby obtaining access to a particular stage (e.g. tertiary education) is conditional on having succeeded in the previous stage (e.g. obtaining a higher secondary education qualification).

Our approach is a methodological middle-ground between the reduced-form treatment

[7]In the previous literature, this approach is defined using a wide range of names: quasi-structural, semi-structural, quasi-reduced form, and black box approach, among others (Colding, 2006; Belzil and Poinas, 2010). We adopt the definition of dynamic treatment effects, as in Heckman and Navarro (2007) and Heckman et al. (2016, 2018a, 2018b).

effect approach and the more structural dynamic discrete choice model approach: while agents are presumed to make choices and account for the consequences of these choices, as is the case in a fully structural approach, we do not need to explicitly identify and model the rules driving these choices, as in a reduced-form approach (Heckman and Navarro, 2007; Heckman et al., 2016, 2018a, 2018b). Hence, while it is not possible to estimate ex-ante individual valuations or expectations, our model leaves to door open to a broader set of explanations about what drives these choices than just perfectly forward-looking behavior (Heckman and Navarro, 2007; Belzil and Poinas, 2010; Heckman et al., 2018a, 2018b). Another major advantage to this approach is that it does not require imposing assumptions on the functional forms or distribution of the unobservables (Heckman et al., 2018a, 2018b). Moreover, this approach allows us to decompose the treatment effects into both direct and total effects associated with later educational choices (Heckman and Navarro, 2007; Heckman et al., 2016, 2018a, 2018b).

Our model includes in total 17 sequential outcomes. First, we include (i) the delay at the start of primary education and (ii) the delay at the start of secondary education. Next, we model the enrolment, track choice and attainment with respect to each of the four considered stages in secondary and tertiary education: (iii) enrolment and track choice at the start of lower secondary education, (iv) lower secondary education attainment, (v) enrolment and track choice at the start of higher secondary education, (vi) higher secondary education attainment, (vii) enrolment and track choice at the start of lower tertiary education, (viii) lower tertiary education attainment, (ix) enrolment and track choice at the start of higher tertiary education, and (x) higher tertiary education attainment. Enrolment and track choice at the start of each of the four stages of one's educational career is modeled as one and the same choice to preserve the sequentiality of the model. To this end, we rely on an ordered logit specification, with outcome value 2 indicating enrolment in the general or academic track, outcome value 1 indicating enrolment in another track, and outcome value 0 indicating no enrolment. Further, as illustrated in Figure 2, access to each of the choices related to these four educational career stages (choices iii to x) is presumed to be conditional on the preceding educational choice: being able to obtain a degree at level j is conditional on having enrolled and chosen a track at the same level, while being able to enrol and choose a track at level j is conditional on obtaining a degree at level $j-1$. Finally, we model the following seven labour market outcomes: (xi) overeducation at the start of the first job, (xii and xiii) a wage selection equation and the natural logarithm of wages at age 23, (xiv and xv) a wage selection equation and the natural logarithm of wages at age 26, and finally, (xvi and xvii) a wage selection equation and the natural logarithm of wages at age 29.

The full sequence of outcomes is represented by O and defined as $O = \{1, ..., S\}$, where each number corresponds to an outcome o, $o \in O$, with a total of S steps. For the sake of clarity, we denote $o = 11$ as $o = OE$, the overeducation outcome, and $o = \{13, 15, 17\}$ as $o = Wage_a$ for $a \in \{23, 26, 29\}$, the wage outcome measured at age a.

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

$$\hat{c}_i^o = c \in C^o \text{ if } \omega_c^o < U_{i,c}^o \leq \omega_{c+1}^o \tag{11}$$

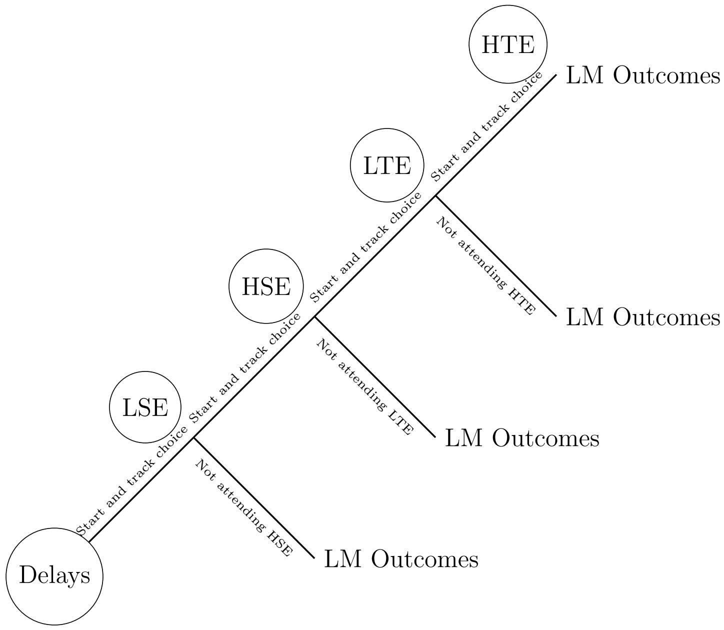
, where $U_{i,c}^o$ is the latent utility of choice c for outcome o, and ω_c^o and ω_{c+1}^o are threshold utilities (*cut-off values*) that determine the ordered choice. In line with the literature, we approximate $U_{i,c}^o$ by a linear index:

$$U_{i,c}^o = \beta_0^o + Z_i\beta_Z^o + R_i^o\beta_R^o + V_{i,c}^o\beta_V^o + v_{i,c}^o \tag{12}$$

In this equation, β_0^o is a constant, Z_i is a vector representing the exogenous variables as observed for individual i, R_i^o captures the unemployment rate at the district level at the moment of outcome o, V_i^o is a vector of endogenous variables, and $v_{i,c}^o$ is a term that is unobservable from the econometrician's point of view.

The vector of endogenous variables, V_i^o, includes all realized outcomes before outcome o, with the exception of three cases. First, by construction, this vector does not include any of the previous outcomes that act as a selection variable for outcome o. This is the case for the four enrolment dummies which act as selection variables for the subsequent educational outcomes, and for the selection dummies related to the wage equations. Second, in the wage equations, we do not include wages at earlier ages as determinant(s). We made this decision as wages are not consistently observed across all ages for all cohorts. The estimated effects in these wage equations are thus to be interpreted as reduced form effects that also take into account indirect effects through prior wages. Finally, as discussed in the next section, delay at the start of primary education, is not added as a direct determinant of the labour market outcomes.

Figure 2: A sequential dynamic model



Notes: Delays includes both Delay in Primary Education and Delay in Secondary Education, Lower Secondary Education (LSE), Higher Secondary Education (HSE), Lower Tertiary Education (LTE) and Hihger Tertiary Education (HTE) includes start, track choice and acquiring a degree. At last, Labour Market (LM) Outcomes include overeducation at the first job, wage selection and log-wage equation for ages 23, 26 and 29.

5.2 Selection bias and identification

If not adequately addressed, two different types of selection bias may emerge when estimating our model. First, there is classical selection bias resulting from the fact that the treated individuals may differ from the control group in a number of respects that are not covered by the observable exogenous variables. For instance, individuals that managed to attain a particular educational degree are likely to be different in terms of abilities and motivations relative to those who dropped out. In case these abilities and motivations also drive labour market outcomes, this would lead to a biased estimate of the labour market return to this degree. Second, the estimates may be biased due to dynamic selection bias. This is due to the increasing negative correlation between a treatment and the unobservable characteristics as students progress their educational careers (Cameron and Heckman, 1998). For instance, even if the selection into lower secondary education were aselective, this is unlikely to be the case for the selection into the subsequent stages of the educational system. Accordingly, among those who did not enrol into the subsequent stage, those who did enrol in lower secondary education would nonetheless be different in terms of unobservables from those who did not enrol in lower secondary education. The implication is that the estimated labour market effects of enrolling in lower secondary education conditional on enrolment in higher secondary education would nonetheless be biased.

To account for these two types of biases, we apply the following factor structure to the error term $v^o_{i,c}$:

$$v^o_{i,c} = \omega^o_k \eta_k + \varepsilon^o_{i,c} \tag{13}$$

in which η_k is a random effect, independent of $\varepsilon^o_{i,c}$, and independent across individuals, and in which ω^o_k is an outcome-specific parameter related to this random effect. This random effect captures determinants that are unobserved and assumed to be independent of the observed exogenous individual characteristics (Z_i and R^o_i). This approach is similar to the one that was adopted by Cameron and Heckman (1998, 2001) to account for dynamic selection. Moreover, as all the treatments of interest (i.e. educational attainment and overeducation) are themselves modelled as outcomes of earlier choices (and, therefore, also as being dependent on the unobserved random effect), our approach also accounts for the former, more classical selection problem[8].

Following the literature on dynamic discrete choice models, we deploy a finite mixture distribution to model the unobserved random variable η_k (cf. Heckman and Singer, 1984; Arcidiacono, 2004)[9]. We assume that this distribution is characterised by an a priori unknown number of K different heterogeneity types with type-specific heterogeneity parameters ω^o_k for each outcome[10]. This avoids relying on strong distributional assumptions and, therefore, also minimizes any bias resulting from misspecification in this respect (Heckman and Singer, 1984; Hotz et al., 2002).

To identify this unobserved component and, ipso facto, the treatment effects of interest, we rely on two different sources of information (cf. Heckman and Navarro, 2007; Heckman et al., 2016, 2018a, 2018b). First, we exploit the panel structure of the data by hinging

[8] This is different for selection problems related to Z_i and R^o_i, as the random effect is assumed to be independent of these variables. However, this is not a problem as the effects of these variables are not the focus of our paper.

[9] It enters each likelihood contribution as a constant parameter, but, given the probability weight for each observation, it becomes a dummy capturing type-specific shocks.

[10] See footnote 5.

on the assumption that all treatments and outcomes are part of the same, more general human capital decision making process. This implies we have to solve an initial conditions problem (Keane and Wolpin, 1997; Cameron and Heckman, 1998, 2001; Keane et al., 2011). In the context of our model, this refers to the fact that this process may already have been initialised prior to enrolment in lower secondary education, which is the earliest choice of interest in the model. Hence our decision to start the model already with delay at the start of primary school (i.e. at the age of six) as the first outcome. This assumption related to the initialisation of the process is substantially weaker compared to assumptions made in many earlier studies using the same methodology (see, e.g. Hotz et al. 2002; Adda et al. 2010). Another implication is that the identification can be facilitated by adding to the model also other decisions that are a crucial part of this decision process but are beyond the scope of the analysis (Cockx, Picchio, and Baert, 2017). Hence our decision to model also the track choice, which is strongly selective in Flanders and generally considered to be an important determinant of subsequent educational and labour market outcomes.

As a second source of identification, we follow Arcidiacono (2005), Heckman and Navarro (2007), Heckman et al. (2016, 2018a, 2018b) and Ashworth et al. (2021) by also adding a set of exclusion restrictions. First, as the unemployment rate at the district level is a time-variant variable, the unemployment rate related to a specific outcome acts, de facto, as an exclusion restriction for the subsequent outcomes (cf. Heckman et al., 2018a, 2018b; Ashworth et al., 2021). Second, we add the delay at the start of primary education as an explanatory variable for the subsequent educational outcomes but not for the labour market outcomes (cf. Baert, Neyt, Omey, and Verhaest, 2022). We thus presume the delay in primary education to affect the labour market outcomes only indirectly through its effect on the delay at the start of secondary education. As the labour market effects of delay at the start of secondary education are unlikely to depend upon when it took place, this is a reasonable assumption.

5.3 Maximization and model selection

If we knew the probability types, the likelihood of the model would be completely separable and we could estimate the entire model in stages. However, since these are unobserved to the econometrician, the estimation of this model is done by using an Expectation-

Maximization (EM) algorithm (Arcidiacono and Jones, 2003). This method was originally developed by Dampster et al. (1977), and applied to DDC models by, amongst others, Arcidiacono and Miller (2011). This method is composed of (i) an expectation and (ii) a maximization step. These two steps are repeated until convergence is achieved.

In the expectation step, we compute the probability of each individual being in each heterogeneity type k, based on the likelihood value for each $k \in K$: $\mathcal{L}_i(Z_i, R_i, V_i, \omega_k; \theta)$. Indeed, for each type k, we know the type-specific likelihood and the total expected likelihood weighted by the probability of being in each type k, $\pi_{k,i}$:

$$\mathcal{L}_i(Z_i, R_i, V_i, \omega_k; \theta) = \sum_{i=1}^{I} \ln \left(\sum_{k=1}^{K} \pi_{k,i} \prod_{o=1}^{O} \mathcal{L}_i^o(Z_i, R_i^o, V_i^o, \omega_k; \theta) \right) \tag{14}$$

Bayes' rule implies that the probability for individual i of being a type k, conditional on the observed variables, endogenous outcomes and unobservables, is:

$$\hat{p}_{k,i}(k|Z_i, R_i, V_i, \pi) = \frac{\pi_{k,i}\mathcal{L}_i(Z_i, R_i, V_i, \omega_k; \theta)}{\sum_{k=1}^{K} \pi_{k,i}\mathcal{L}_i(Z_i, R_i, V_i, \omega_k; \theta)} \tag{15}$$

In the maximization step, the conditional probabilities of being heterogeneity type k are treated as given, which allows us to optimize the full model by maximum likelihood. Note that, as Arcidiacono and Jones (2003) show, the maximization step can be now carried out in stages: indeed, once we treat the heterogeneity probabilities as given, the likelihood is again fully separable, as mentioned at the beginning of this section.

$$\sum_{i=1}^{I} \sum_{k=1}^{K} \hat{p}_{k,i}(k|Z_i, R_i, V_i, \pi) \left(\sum_{o=1}^{O} \ln(\mathcal{L}_i^o(Z_i, R_i^o, V_i^o, \omega_k; \theta)) \right) \tag{16}$$

After the maximization step, we update the conditional probabilities and iterate to the next maximization. This process is repeated until convergence is obtained.

To identify the optimal number of heterogeneity types k, we re-estimate the model by gradually adding up to four types to the model. In Table 5, we report the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) values on each of these models. Based on these criteria, we select the model with three heterogeneity types ($K = \{1, 2, 3\}$) as our benchmark model. The proportions of the three types are 27.5%, 6.4% and 66.3% respectively. Moreover, to further ease the computational burden, we force $\eta_{k=1} = 0$. Hence, we need to estimate the heterogeneity parameters only for types

$k = 2$ and $k = 3$. For $k = 2$ and $k = 3$, η_2 and η_3 enter the likelihood function as an additional intercept.

Table 5: Model selection using AIC and BIC

Model:	Number of parameters	Log-likelihood	AIC	BIC
K1	340	-35674.28	72028.55	72678.56
K2	357	-32152.00	65018.00	65700.51
K3	374	-29770.49	**60288.98**	**61003.99**
K4	391	-29778.63	60339.28	61086.79

Notes: Each model is named after Kn, with $n \in \{1, 2, 3, 4\}$, which is defined, as in this section, using the mathematical notation of k unobserved types. Therefore, Kn represents the model with n heterogeneity types.

5.4 Counterfactual simulation

To gauge the treatment effects of interest and their confidence intervals, we rely on a counterfactual simulation strategy (Cockx, Picchio, Baert, and 2019). In each of the 999 draws of the simulation, the parameters used are randomly drawn from the asymptotic normal distribution of the model's parameters. Subsequently, for each of these draws, the probability types, estimated using the EM algorithm, are used to assign a heterogeneity type to each individual in the sample randomly. Thereafter, based on these novel set of parameters, we simulate the full sequence of schooling and labour market outcomes for each individual in the sample.

This counterfactual simulation strategy is also used to assess the quality of the model, by generating the full set of outcomes and comparing it to the observed outcomes in the data. This is included in Table 6. The observed probabilities are in most cases within the 95% confidence bounds of the simulated probabilities. The model thus fits quite well the observed outcomes in the dataset.

A similar simulation strategy is adopted to gauge the composition of the three heterogeneity types. Table 7 displays the simulated outcomes when forcing all individuals to be one of the three heterogeneity types, labelled as Type 1, 2 or 3. With respect to the two main types, a clear pattern emerges with Type 1 individuals having (relatively to

Table 6: Goodness of fit

Variables	**Observed**	Simulation	95% CI	
(a) Delays:				
Delay in Primary Education	**0.015**	0.017	0.014	0.020
Delay in Secondary Education	**0.101**	0.104	0.097	0.111
(b) Educational choices:				
Start and Track Choice in LSE	**2.515**	2.508	2.498	2.518
LSE	**0.954**	0.952	0.948	0.957
Start and Track Choice in HSE	**2.379**	2.374	2.363	2.386
HSE	**0.887**	0.886	0.879	0.892
Start and Track Choice in LTE	**1.852**	1.852	1.837	1.867
LTE	**0.486**	0.489	0.478	0.499
Start and Track Choice in HTE	**1.361**	1.383	1.368	1.399
HTE	**0.194**	0.206	0.197	0.214
(c) Labour market outcomes:				
Overeducation	**0.353**	0.349	0.338	0.359
Wage Selection at 23	**0.539**	0.527	0.518	0.536
Log-hourly wage at 23	**1.974**	1.982	1.979	1.985
Wage Selection at 26	**0.414**	0.413	0.409	0.417
Log-hourly wage at 26	**2.072**	2.076	2.072	2.080
Wage Selection at 29	**0.385**	0.381	0.376	0.386
Log-hourly wage at 29	**2.126**	2.126	2.121	2.130

Notes: Educational attainments are defined as Lower Secondary Education (LSE), Higher Secondary Education (HSE), Lower Tertiary Education (LTE), Higher Tertiary Education (HTE). 95% CI indicated the 95 percent confidence intervals, as simulated using our approach.

Type 3 individuals) a higher probability to experience delay at the start of primary and secondary education, a lower probability to obtain each level of educational attainment, a higher probability of being overeducated, and a lower average wage. This is consistent with Type 1 individuals being of lower ability relative to Type 3 individuals. Type 2 individuals, which are much less prevalent in the data, seem to be a more specific category, as they combine a high probability of overeducation with high wages.

Table 7: Probability types simulated models

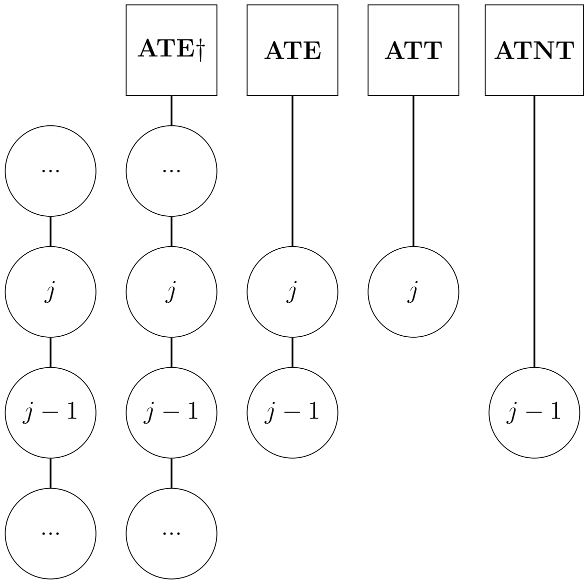
	Overall	Type 1	Type 2	Type 3
		27.40%	*6.40%*	*66.20%*
(a) Delays:				
Delay in Primary Education	**0.017**	0.022	0.021	0.014
Delay in Secondary Education	**0.104**	0.127	0.110	0.095
(b) Educational choices:				
LSE	**0.952**	0.939	0.946	0.963
HSE	**0.886**	0.840	0.871	0.910
LTE	**0.489**	0.381	0.416	0.537
HTE	**0.206**	0.130	0.194	0.233
(c) Labour market outcomes:				
Overeducation	**0.349**	0.373	0.405	0.339
Log-hourly wage at 23	**1.982**	1.964	2.155	1.977
Log-hourly wage at 26	**2.076**	1.471	2.430	2.052
Log-hourly wage at 29	**2.126**	1.554	2.441	2.110

Notes: Educational attainments are defined as Lower Secondary Education (LSE), Higher Secondary Education (HSE), Lower Tertiary Education (LTE), Higher Tertiary Education (HTE).

5.5 Treatment Effects

As in Heckman, Humphries and Veramendi (2018a, 2018b), we define different treatment effects for analyzing the impact of educational attainment on overeducation and wages. The first treatment effect to estimate is denoted as ATE†, which is the treatment effect computed over the entire population. This ATE is less relevant from a practical point of view, because dynamic selection causes not everyone to have a reasonable likelihood to reach each level of education. Therefore, we define a more credible treatment effect, ATE, which is computed over everyone at one of the two final nodes. For instance, for the likelihood to be overeducated and the wage returns related to HTE, we compute the treatment effect over those who obtained either an LTE or an HTE as maximum level of educational attainment.

Figure 3: Definition of treatment effects



Notes: The first column represents the full sample, including individuals at j and $j-1$ and individuals included in other nodes (represented by circles containing "..."). Individuals are included in a given j educational attainment and in $j-1$ (i.e. the lower educational attainment, e.g. if j=HTE, then j-1=LTE). As described in the main text, ATE† is computed over the full sample, ATE over the individuals at the final nodes (j and $j-1$), ATT over individuals in j and ATNT over individuals in $j-1$.

Furthermore, by calculating this separately over those with the treatment level of educational attainment and those with a level of educational attainment that is one level below the treatment level, we can also define the average treatment effect on the treated (ATT) and the average treatment effect on the non-treated (ATNT) (e.g. when the treatment is obtaining a HTE, ATT for those that obtained a HTE and ATNT for those with a LTE). The difference between ATT and ATE are a measure of sorting on gains, while the difference between ATNT and ATE are a measure of sorting on losses (Heckman et al., 2018a, 2018b).

These definitions are summarized in Figure 3, where j represents the treatment level of educational attainment and $j-1$ represents one level below this treatment level (e.g.

if j is college, $j-1$ is high-school). The circles indicate which part of the sample is taken into account for the calculation of each of the treatment effects.

Finally, besides differentiating between ATE†'s and ATE's, we also differentiate between direct ATE's and total ATE's, with total ATE's also taking into account that a level of educational attainment allows to enrol in programs at higher levels of educational attainment and, henceforth, also may generate indirect effects in this way.

6 Results

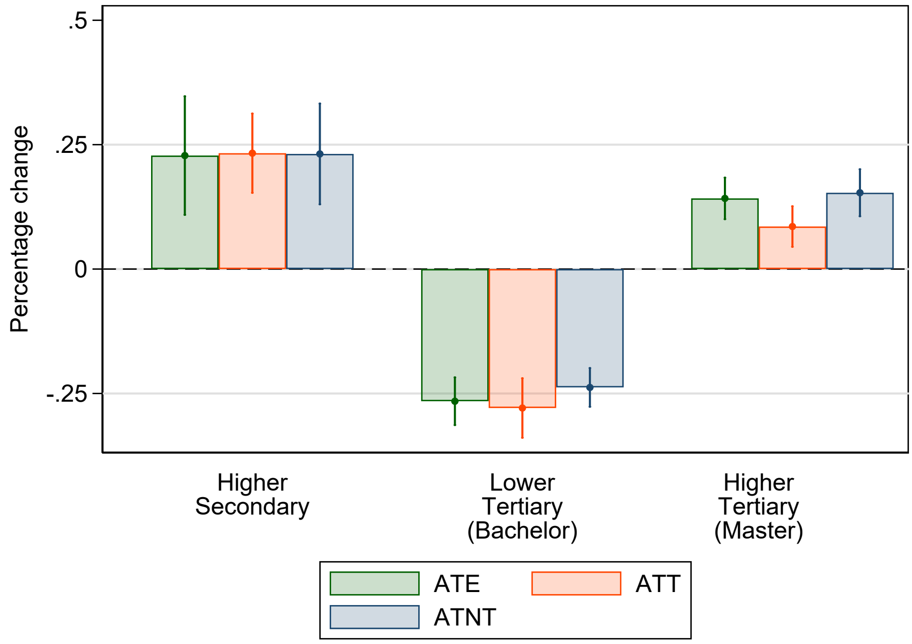
In this section, we present the simulated treatment effects of interest. First, we present results on the impact of educational attainment on overeducation. Second, we report the results on the wage returns conditional on one's match status as well as on the wage penalty to overeducation. Third, we simulate average unconditional wage returns to education and use the results in the preceding subsections to decompose these unconditional returns into various components. Fourth, we also look into how overeducation generates heterogeneous wage returns. All of these simulations are based on our preferred model, of which the full set of estimated parameters is reported in the Appendix C. In our description, we mainly focus on the direct ATE's and point to the main differences with the other definitions of treatment effect. In a last subsection, we also present some sensitivity analyses by relying on alternative sets of estimations.

6.1 Overeducation and educational attainment

Figure 4 shows the ATE of each of the considered levels of education on overeducation, conditional on having obtained the preceding level of attainment. For instance, the effect of a Master's degree represents the effect relative to having obtained a Bachelor's degree only.

The effect is clearly non-linear in the level of educational attainment. While entering the labour market with a high school degree (HSE) is found to increase one's chances to be overeducated relative to entering the labour market with a lower secondary degree (LSE) only, the opposite is true with respect to a Bachelor's degree (LTE) relative to a high school degree (HSE). Both effects are quite substantial, with a high school diploma increasing one's likelihood to be overeducated by about 22 percentage points and a Bache-

Figure 4: Impact of educational attainment on overeducation (ATE, ATT and ATNT)

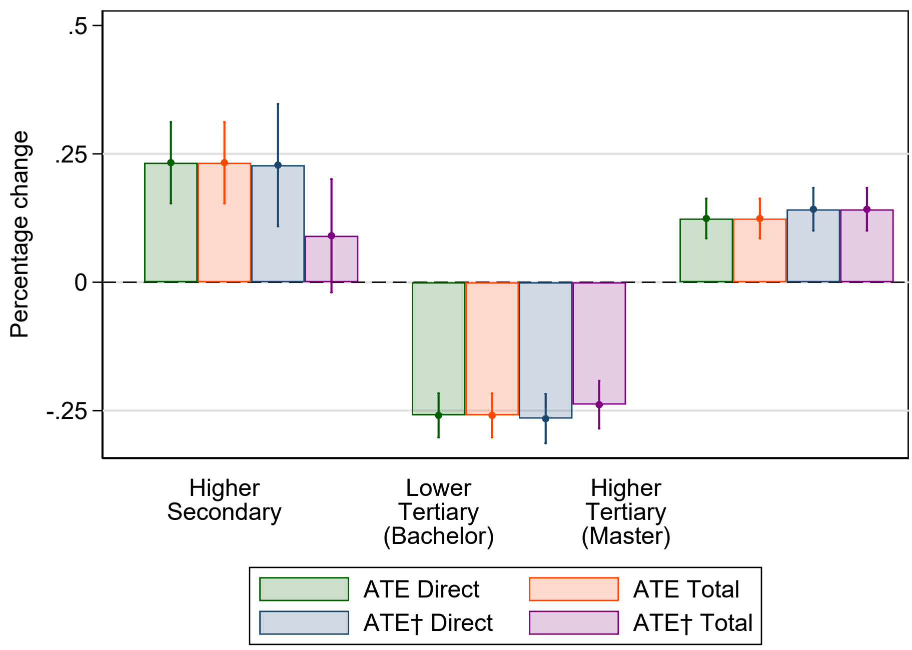


lor's degree lowering this likelihood by about 25 percentage points. Finally, investing also in a Master's degree again increases one's overeducation probability relative to having obtained a Bachelor's degree only. However, as the latter effect is estimated to be about 11 percentage points only, a master's degree still reduces one's likelihood to be overqualified relative to a high school degree by about 14 percentage points. These outcomes are clearly in line with a polarized labour market and challenge the idea that overeducation is mainly a problem among tertiary education graduates.

In Figure 4, we further differentiate between the ATT and the ATNT. In line with Heckman et al. (2018a, 2018b), we find evidence of sorting on gains at the higher stages of the educational career. Individuals sort on their expected benefits from obtaining a tertiary education degree in terms of experiencing lower levels of overeducation. This may be attributed to high-ability individuals expecting better-matched and, henceforth, better-paid jobs when participating in higher education.

Finally, in Figure 5, we also look at how the estimated effects change when the sample is extended beyond the final nodes (ATE†) and when total, instead of direct effects, are considered. For the Bachelor's and Master's levels, the results are largely similar. The treatment effect of starting and obtaining an HSE, meanwhile, is clearly lower when the total ATE† effect is considered. This is driven by the dynamic nature of our model, since obtaining an HSE degree does not only directly increase one's risk of overeducation, but also grants access to higher levels of educational attainments that are associated with a lower risk of overeducation. The difference in outcomes between the total ATE and total ATE† is in line with the aforementioned sorting on gains: those for which the effect of obtaining a higher education degree on overeducation is lower are more likely to select themselves into higher education and are, therefore, less likely to be included in the calculation of the ATE with respect to obtaining an HSE.

Figure 5: Impact of educational attainment on overeducation (ATE and ATE†, Direct and Total effects)



6.2 Conditional wage returns to education

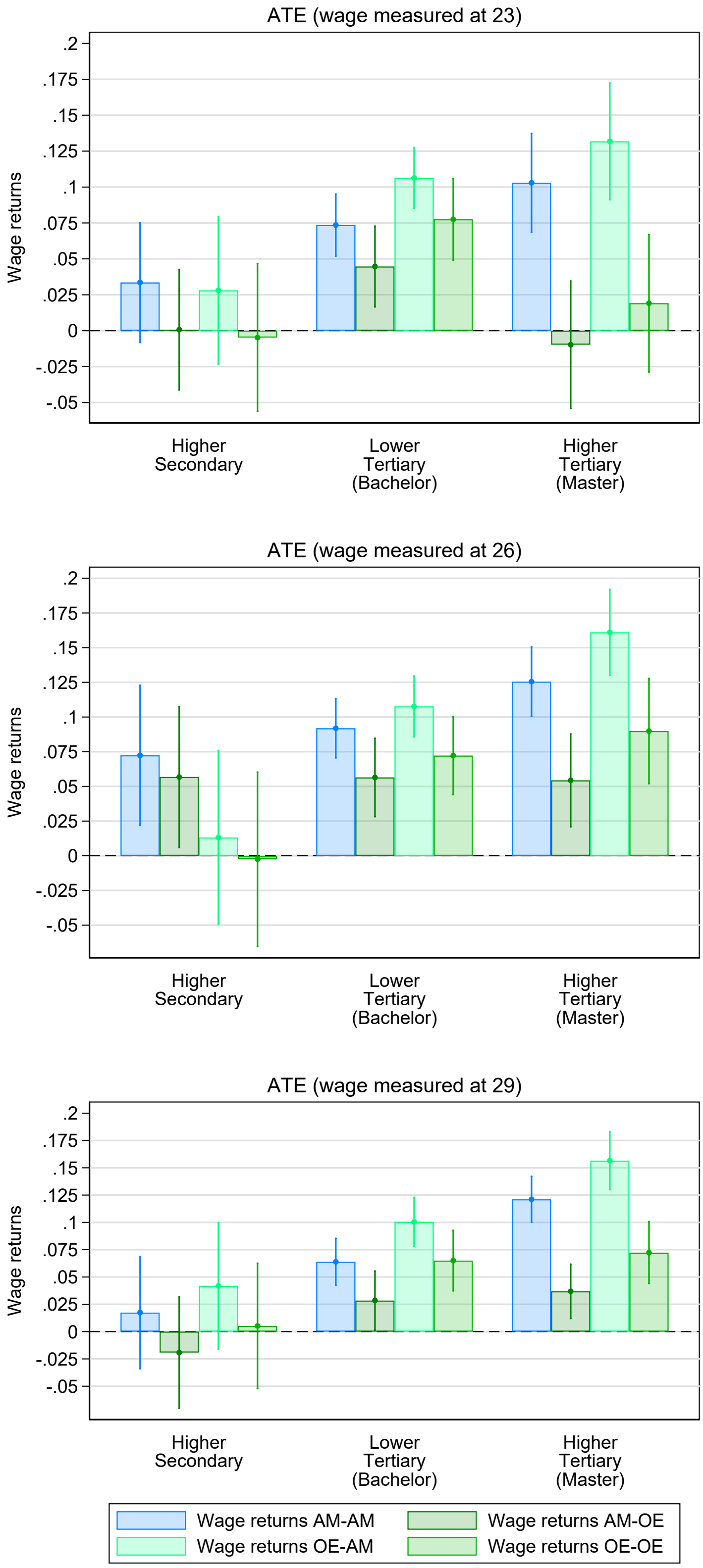
In Figure 6, we report the direct ATE on wages depending on one's match status at the attained level of education (j) and the match status one may have obtained at the preceding level ($j-1$). This delivers the following four conditional returns: (a) the wage return when being adequately matched in both j and $j-1$, (b) the wage returns to overeducation at level j while being adequately matched at level $j-1$, (c) the wage return to being adequately matched when starting from an overeducation status and, at last, (d) the wage return when being overeducated in both j and $j-1$. These conditional returns are reported for each of the three wage observations.

The first type of conditional return (a), which is the return to educational attainment assuming one is always perfectly matched, is found to gradually increase by level of educational attainment. For instance, at age 23, the wage returns to obtain a higher secondary, a lower tertiary and a higher tertiary education degree presuming one is always adequately matched are 3.4%, 7.4% and 10.3% respectively. At age 29, these conditional returns are 1.7%, 6.4%, and 12.1% respectively. Also the second type of wage return (b), which is the one conditional on being overeducated at level j and being adequately matched at the preceding level is, in most cases, positive. Nonetheless, we find this return to be consistently lower than the return conditional on being adequately educated at both levels of attainment. For instance, at age 29, the wage return to obtaining a higher tertiary degree (relative to a lower tertiary degree) is estimated to be equal to 3.7% only in case this additional investment induces one to become overeducation.

These first two types of conditional returns are equivalent to the wage return to adequate education (a) and the return to overeducation (b) as usually reported in the literature on overeducation. Moreover, by subtracting these returns, we obtain the results on the overeducation wage penalty, which are reported in supplementary Figure 7, these penalties are statistically significant at each age and at each level of educational attainment. At age 23, these penalties range from 2.9% for those with a bachelor's degree to 11.3% for those with a master's degree. The latter penalty drops somewhat to 8.4% if measured at the age of 29. Note that these effects represent the effects of the match status at the start of the first job. Therefore, besides indicating that the overeducation penalty is real, these findings also suggest initial overeducation generates a long-lasting scarring effect.

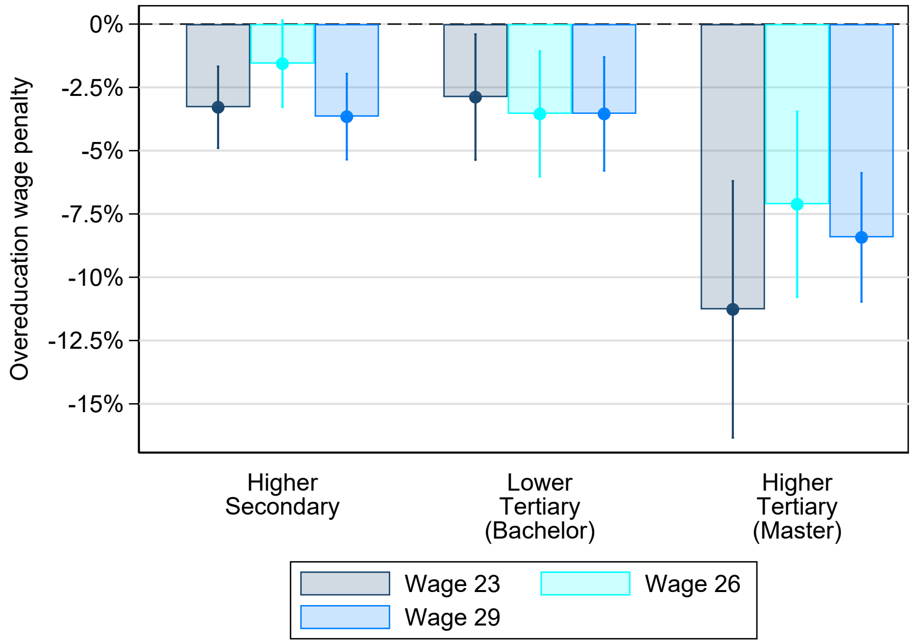
Investing in more education may not only induce people to stay adequately educated or to become overeducated, but also to improve their match status (case (c)) or to stay overeducated (case (d)). As shown in Figure 6, also the wage returns conditional on these match statuses are usually positive, at least when it concerns investment in tertiary education. For instance, at age 29, we find the wage return to a higher tertiary education degree (relative to a lower tertiary degree) to be equal to 15.7% in case one also manages to improve one's match status through this investment. Similarly, the return to a higher tertiary education degree is still 7.2% for overeducated workers in case this additional

Figure 6: Conditional wage returns (at 23, 26 and 29 years)



Notes: we simplify the notation from Equations 2, 3, 4 and 5 and we refer to: (i) Wage returns AM-AM as $\Omega^{M,M}_{a,i,j}$, (ii) Wage returns AM-OE as $\Omega^{M,O}_{a,i,j}$, (iii) Wage returns OE-AM as $\Omega^{O,M}_{a,i,j}$ and (iv) Wage returns OE-OE as $\Omega^{O,O}_{a,i,j}$.

Figure 7: Overeducation Wage Penalty by educational attainment



investment would have induced one to stay overeducated. Moreover, while the former conditional return well exceeds the return conditional on being adequately educated at both the considered and the preceding level of attainment, the latter return usually exceeds the return for those who become overeducated. Henceforth, the standard measure of the wage return to education for those who are overeducated may provide an underestimation of their true wage return to education.

In Appendix B, we also report the results on these conditional returns while relying on our alternative treatment indicator ATE† and while also taking into account the indirect effects of additional educational investments on subsequent levels of educational attainment. Overall, our conclusions are largely similar while relying on these alternative treatment effect definitions. The main differences again pertain to the higher secondary education level. Several of the estimated conditional returns to this level of attainment are small and statistically insignificant while relying on the direct ATE definition. This is probably due to labour market institutions such as collective bargaining and minimum wages, which may generate strong wage compression at the lower end of the wage distribution. When relying on the total ATE† definition, however, these returns become much more substantial and statistically significant. Also this result is consistent with the wage returns to a higher secondary education being mainly indirect, as obtaining a higher secondary education degree opens the door towards tertiary education.

6.3 Unconditional wage returns: decomposition

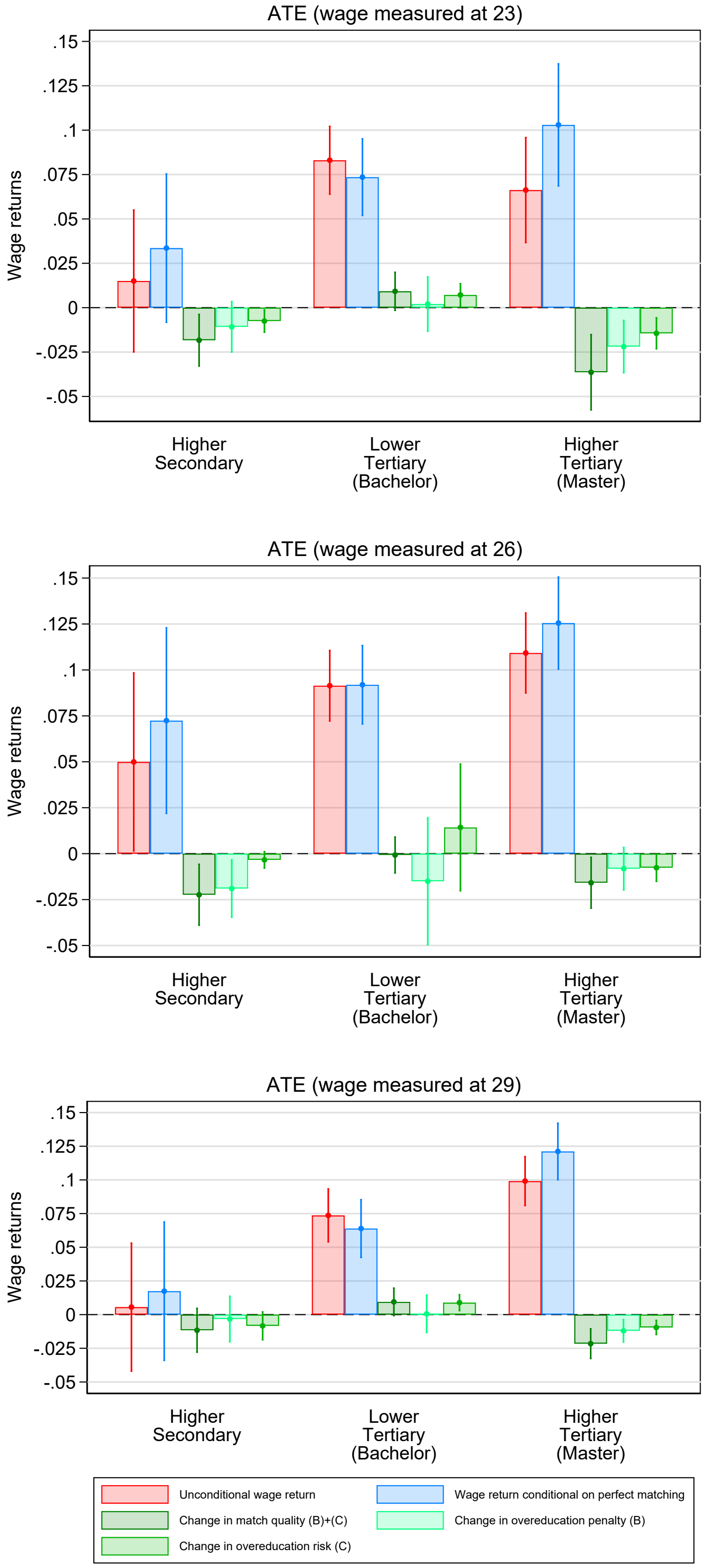
To investigate how overeducation affects the average unconditional wage return, we implement a decomposition approach. In Figure 8, we report this decomposition while relying on the direct ATE definition. While the first bar reports the unconditional return, the next two bars represent its decomposition into one part that reflects the return in the case of fixed match quality across levels of attainment and another one due to changes in match quality. The last two bars represent a further decomposition of the change in match quality component in one subcomponent due to changes in wage penalties to overeducation and another one due to changes in overeducation risk.

While the unconditional wage returns to obtaining a master's degree are consistently positive, they are lower than those in case of perfect matching. For instance, at age 23, the unconditional return is equal to 6.6% relative to a return of 10.3% in the case of perfect matching. Almost two-thirds of this difference (2.2 %-points) is due to the larger overeducation penalty for masters relative to bachelors while the remaining part (1.4 %-points) is due to the larger overeducation risk among masters. Over time, however, this difference clearly drops even if masters also experience a further increase in the wage return to education in case of perfect matching. For instance, at age 29, the unconditional return is equal to 9.9% relative to a return of 12.1% in the case of perfect matching. This is mainly due to a drop in the relative importance of the difference in overeducation penalties between bachelors and masters. Indeed, in the previous section, we reported a clear drop in the overeducation penalty over time for masters.

For bachelors, the results are clearly different, with their unconditional wage return being at least equal (at age 26) or even larger than the wage return in the case of constant match quality across levels of educational attainment. For instance, at age 29, their unconditional wage return is 7.4% relative to a wage return of 6.4% conditional on perfect matching. Our decomposition suggests this is largely due to differences in overeducation probabilities between those with a high school and those with a bachelor's degree. Indeed, in Section 6.1, we reported that investing in a bachelor's degree causes the overeducation risk to drop substantially.

Finally, for obtaining a high school degree, the estimated unconditional returns are

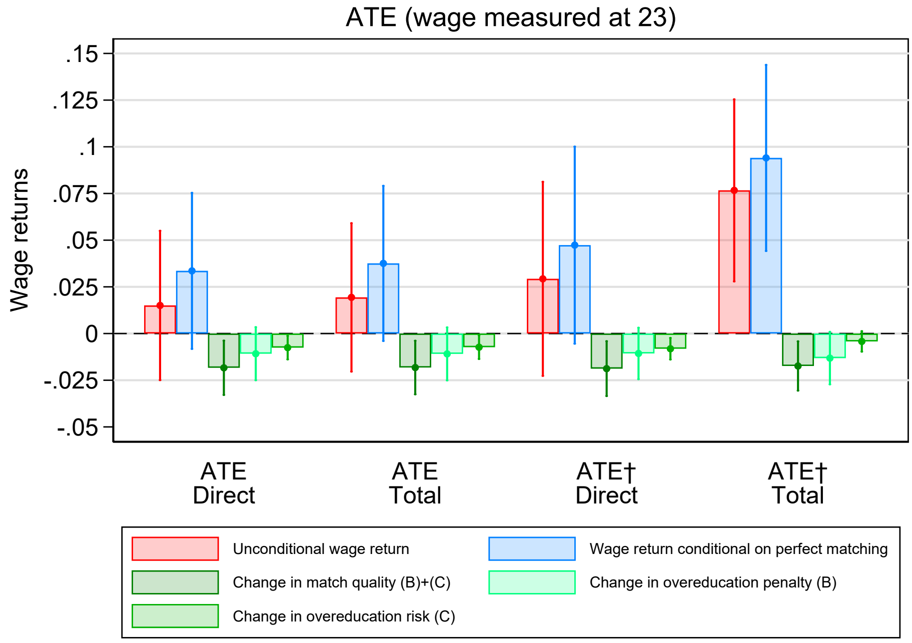
Figure 8: Decomposition of change in match quality



Notes: the decomposition approach is explained in Section 2 and in Equation 10: each bar included in this graph can be referred directly to this equation.

lower but also less precise. Hence, its estimate is only statistically significant at age 26. Besides resulting from a low return in the case of perfect matching, this is also due to a significant drop in match quality relative to when one would have entered the labour market without a high school degree. For instance, at age 23, this drop in match quality is estimated to reduce the average unconditional return by about 1.8 %-points.

Figure 9: Decomposition of change in match quality (ATE and ATE†, Direct and Total effects)

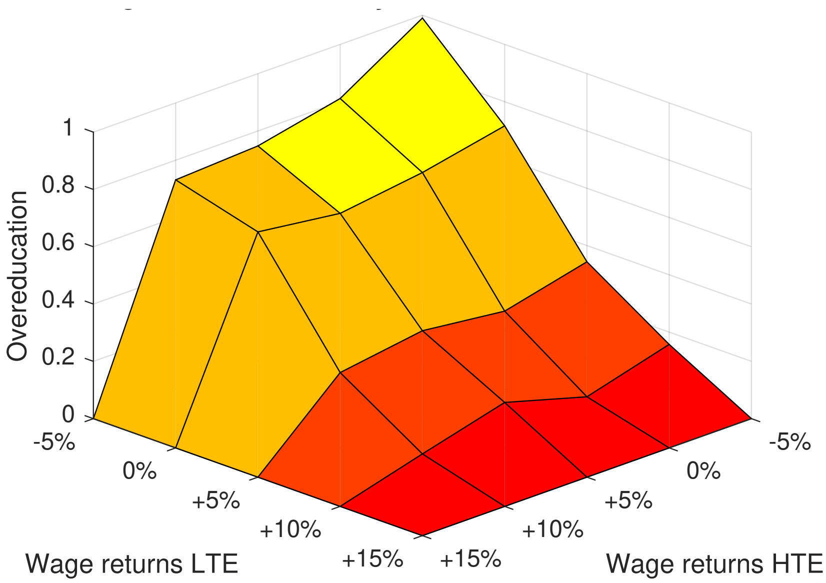


In Figure 9, we further report results on this decomposition for obtaining a high school degree while relying on alternative indicators of the treatment effects. The results are for wages at age 23. The results on these alternative indicators for ages 26 and 29 and for the other levels of educational attainment are reported in Appendix B. As a high school degree provides access to higher education, the results are again more favorable when relying on the total ATE† indicator. While the direct unconditional return is estimated to be equal to 1.5% only when relying on the direct ATE indicator, the total ATE† return is estimated to be 7.7%. This is mainly due to the higher estimated return conditional on perfect matching, which is estimated to be equal to 9.4% relative to 3.4% only when relying on the direct ATE indicator. The estimated effect due to changes in match quality, meanwhile, is fairly similar across the alternative indicators. Even though overeducation penalties are usually larger at higher levels of obtained education, this is leveled out by the lower overeducation risk that is associated with obtaining a higher education degree relative to a high school degree only.

6.4 Heterogenous Wage Returns to Education

As a first indication of how overeducation may be associated with heterogeneous returns to education, Figure 10 compares the simulated overeducation probabilities with the simulated wage returns at age 23 for obtaining a LTE and HTE relative to obtaining a high school degree only. To this end, we rely on the full set of simulated outcomes for all individuals. A clear negative relationship emerges between the predicted risk to be overeducated and the unconditional wage return to higher education. Overall, this is consistent with overeducated individuals having, on average, less favorable traits that reduce their potential benefits of obtaining a higher education degree.

Figure 10: Heterogeneous wage returns and overeducation (conditional on HSE)



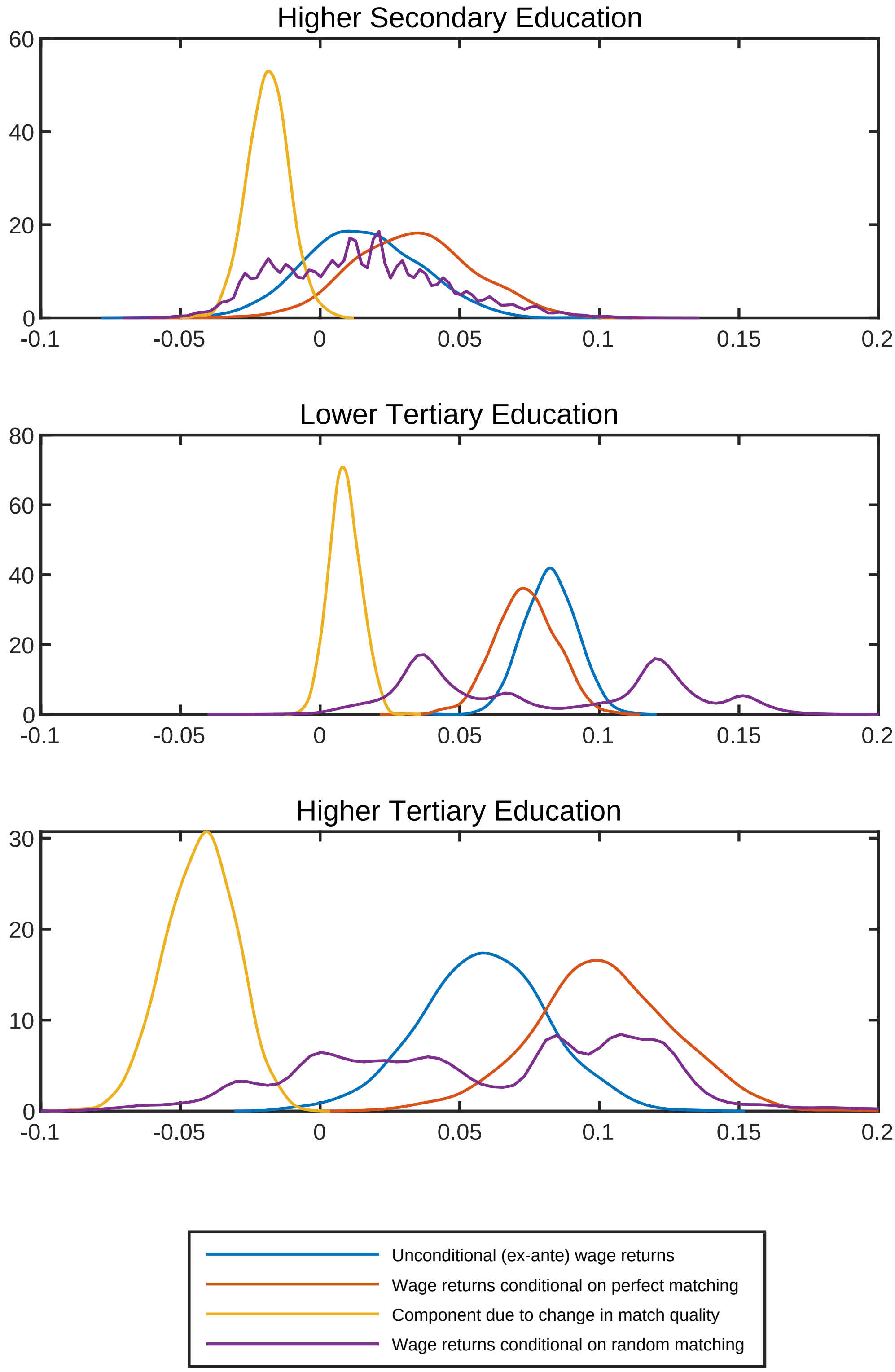
Notes: This figure is obtained using the full sequence of simulated outcomes. In this framework, we discretize wage returns and compute the fraction of overeducated individuals for each composition of the resulting discretized wage returns bins. We use wage returns at the age of 23, so to avoid issues with cohort data

To test whether the differences in overeducation risk across individuals are merely a reflection or also a cause of these heterogeneous returns, we also report, in Figure 11, the simulated between-individual distribution of the unconditional ex-ante wage returns to education along with the simulated between-individual distribution on their two components: the wage returns to education conditional on perfect matching, and the wage components due to changes in match quality. Each observation in the presented distributions represents the expected value of these three variables for one individual in the sample, which are calculated by averaging, within each individual, over their 1000 simulated values. We report separate results by level of educational attainment and concentrate on ATE wage returns at age 23. The results on the other age observations are reported in Appendix B.1.

We first focus on the distributions of the two components. As shown, the between-individual heterogeneity in wage returns conditional on perfect matching is estimated to be substantial. This heterogeneity in conditional returns is the most substantial with respect to obtaining a master's degree and somewhat less pronounced with respect to obtaining a bachelor's degree. Moreover, our model suggests also the expected wage component due to changes in expected match quality to be heterogeneous across individuals, albeit to a lesser extent relative to the heterogeneity in component in case of perfect matching. Further, in line with the results reported in the previous sections, we find this expected component due to changes in match quality to be negative for most individuals with respect to obtaining a high school or a master's degree. With respect to obtaining a bachelor's degree, meanwhile, this component is positive for most individuals.

As expected, we find the between-individual heterogeneity in these two components to also translate in a substantial between-individual heterogeneity in the unconditional wage returns. Nonetheless, this heterogeneity is, for each of the three considered levels of educational attainment, fairly similar to the heterogeneity in returns conditional on perfect matching. Overall, this indicates the differences in overeducation risk to mainly reflect the heterogeneity in unconditional returns rather than to reinforce this heterogeneity. Nonetheless, in line with our findings in the earlier sections, we find overeducation to affect the location of the distributions of unconditional returns. As a result of the negative component due to changes in match quality when obtaining a high school or master's degree, we find the distribution of the unconditional wage return to obtaining such a degree to be situated to the left of the distribution of its returns conditional on perfect matching. This translates in negative unconditional returns for a non-negligible part of the sample. Also the unconditional returns to obtaining a master's degree are clearly lower relative to its returns conditional on perfect matching. Nonetheless, this unconditional

Figure 11: Simulated distributions of unconditional wage returns, their decomposition and realized wage returns (age 23)



return remains substantial for most of the individuals. Finally, in line with the associated improvement in average match quality, we find the unconditional return to obtaining a bachelor's degree to exceed its return conditional on perfect matching for most individuals.

These unconditional expected wage returns partly depend on one's overeducation risk in the treated level of educational attainment relative to the (lower) control level of attainment. However, depending on one's effective match status at each level of attainment, realized (i.e. ex-post) returns may be lower or higher. For instance, even if one has a high risk of overeducation at the treated level of attainment, one may still manage to be adequately matched due to idiosyncratic matching shocks. To test for the impact of this idiosyncratic matching, we also simulate the distribution of ex-post returns that may emerge from a random matching process while relying on the estimated parameters of the model. The resulting distributions are added to the graphs in Figure 11. As shown, the resulting ex-post returns resulting from this simulated random matching are much more heterogeneous relative to the unconditional (ex-ante) returns. This is in particular the case for obtaining a bachelor's and a master's degree. For instance, in the latter case, a substantial proportion realizes a return that is well above the 10% while another part realizes returns that are just as well negative. Overall, this is clearly in line with overeducation being the consequence of search and matching frictions and, henceforth, being a source of heterogeneous ex-post returns to college.

6.5 Sensitivity analyses

We end with two sensitivity analyses related to our model. Our first analysis focuses on the adopted procedure to measure overeducation. This procedure was based on a combination of three independent measures of overeducation. To gauge the impact of this decision, we re-estimate the model based on each of the three separate overeducation wage measures, as described in Section 4.5.

Table 8 includes a selection of ATE's based on these alternative estimates. First, we report results with respect to the impact of educational attainment on the risk to become overeducation. Reassuringly, the direction of the effects is the same across the adopted measures and in line with the benchmark results: while both obtaining a high school degree and a master's degree is found to increase one's chances to be overeducated (relative to obtaining the previous level) based on each measure, obtaining a bachelor's

Table 8: Sensitivity analysis on the overeducation measure

	Educational attainment:	Overeducation measure: **BM**	JA	ISA	DSA
(a) *Effects of Educational Attainment on Overeducation*					
ATE Direct	HSE	**0.228***	0.089	0.226***	0.055
		(0.060)	(0.063)	(0.063)	(0.058)
	LTE	**-0.265***	-0.129***	-0.336***	-0.116***
		(0.024)	(0.023)	(0.025)	(0.020)
	HTE	**0.142***	0.249***	0.106***	0.085***
		(0.021)	(0.019)	(0.020)	(0.017)
(b) *Overeducation Wage Penalty*					
Wage 23	HSE	**-0.033***	-0.031***	-0.019**	-0.031***
		(0.008)	(0.009)	(0.008)	(0.009)
	LTE	**-0.029**	-0.032***	-0.031**	-0.036**
		(0.013)	(0.011)	(0.013)	(0.014)
	HTE	**-0.113***	-0.021	-0.112***	-0.078***
		(0.026)	(0.026)	(0.028)	(0.025)
(c) *Unconditional Wage Returns Decomposition*					
Unconditional WR	HSE	**0.015**	0.004	0.014	0.002
		(0.020)	(0.021)	(0.020)	(0.019)
	LTE	**0.083***	0.080***	0.087***	0.073***
		(0.010)	(0.010)	(0.010)	(0.009)
	HTE	**0.066***	0.060***	0.065***	0.078***
		(0.015)	(0.015)	(0.015)	(0.014)
WR conditional on PM	HSE	**0.034**	0.024	0.027	0.008
		(0.021)	(0.023)	(0.022)	(0.019)
	LTE	**0.074***	0.077***	0.083***	0.071***
		(0.011)	(0.012)	(0.011)	(0.010)
	HTE	**0.103***	0.061**	0.093***	0.092***
		(0.018)	(0.024)	(0.016)	(0.015)
Change in MQ	HSE	**-0.019***	-0.020**	-0.013	-0.007*
		(0.007)	(0.010)	(0.008)	(0.003)
	LTE	**0.010***	0.003	0.004	0.002
		(0.006)	(0.007)	(0.006)	(0.003)
	HTE	**-0.037***	-0.000	-0.028***	-0.014**
		(0.011)	(0.019)	(0.009)	(0.007)

Notes: The overeducation measures represent respectively: the Benchmark Measure (BM), Job Analysis (JA), Indirect Self-Assessment (ISA) and Direct Self-Assessment (DSA). Educational attainments are defined as: Higher Secondary Education (HSE), Lower Tertiary Education (LTE, or Bachelor) and Higher Tertiary Education (HTE, or Master). At last, the measures used in the decomposition are the following: unconditional (ex-ante) wage returns (Unconditional WR), wage return conditional on perfect matching (WR conditional on PM) and change in match quality (Change in MQ).

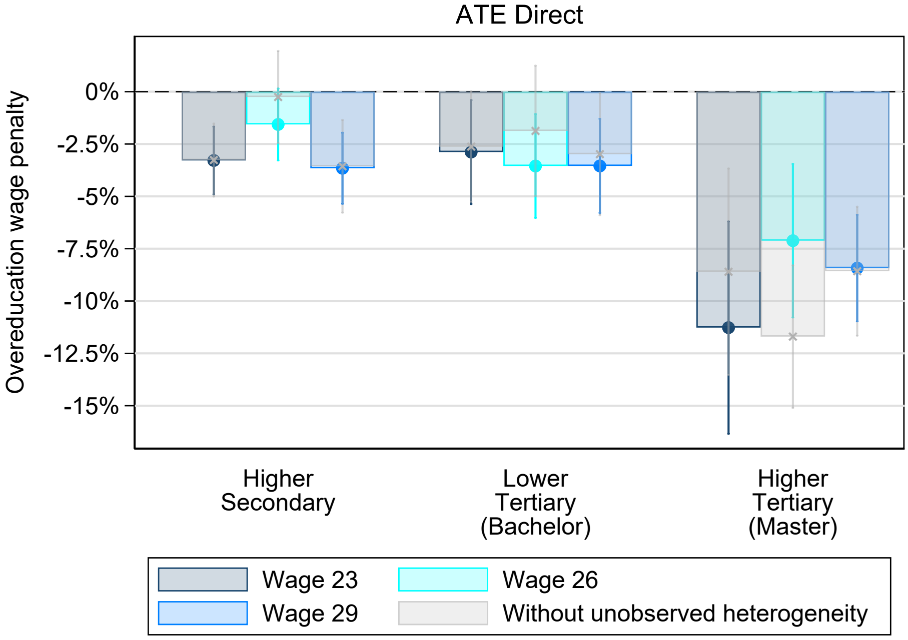
degree is always found to be associated with a lower overeducation risk. Nonetheless, the estimated effects are different in size across the various measures and, in two cases with respect to obtaining a high school degree, also statistically insignificant. Second, also the finding of a wage penalty to overeducation is fairly consistent across all measures and levels of attainment. Only with respect to obtaining a master's degree while relying on the job analysis measure, this penalty is estimated to be statistically insignificant. Nonetheless, these penalties are often smaller when relying on the independent measures relative to those when relying on the benchmark measure. Third, also the results on the decomposition are fairly consistent, with the change in match quality negatively affecting the unconditional return to a high school and master's degree and positively affecting the return to a bachelor's degree. Also for this analysis, however, the size of the estimated ATE's depend on the adopted measures with the benchmark measure usually delivering more sizeable and statistically significant estimates on both components of the unconditional wage return. For instance, unlike when relying on the benchmark measure, the other measures do not generate a statistically significant component of the unconditional wage return to obtaining a bachelor's degree that is attributed to a change in match quality.

Overall, these results show that, while not leading to radically different conclusions, the choice of our measure matters for the magnitude of the estimated effects. As argued in the method section, we believe our benchmark measure to be more accurate and, henceforth, to deliver less biased estimates. In any case, our finding that the benchmark measure often produces stronger overeducation wage penalties as well as stronger effects on both components in the wage decomposition, is consistent with the other three measures being more prone to random measurement errors.

As a second sensitivity analysis, we test for whether accounting for unobserved heterogeneity matters. To this end, we re-estimate our model while considering one heterogeneity type only. The results on the wage penalty to overeducation are summarized in Figure 12. With the exception of the estimates with respect to wages at age 29 when having obtained a master's degree, we find that not accounting for unobservables either hardly affects the estimated wage penalty to overeducation or even leads to an underestimation has no effect on the estimate.

At first sight, this seems surprising as our results suggested overeducated individuals to

Figure 12: Overeducation Wage Penalty: sensitivity analysis on unobserved heterogeneity



Notes: Overeducation wage penalty by educational attainment computed for both model without unobserved heterogeneity (in grey) and the benchmark model with three heterogeneity types.

have less favorable traits and lower expected unconditional returns to education. However, besides accounting for classical unobserved heterogeneity, our models also account for dynamic selection. As shown in Table 7, individuals of Type 3, which combine the highest levels of educational achievement with the lowest risk to be overeducated (see Section 5.4), are also more likely to be selected in the wage equations. And the opposite is true for individuals of Type 1, which combine lower levels of educational attainment with a more elevated risk of overeducation. A likely explanation for this selection is that individuals with less favorable traits are less inclined to take up jobs as the offered wages in these jobs are less likely to exceed their reservation wage. This effect may be enforced if job seekers are also more reluctant to take up jobs for which they are overeducated. The estimates on the overeducation wage penalty thus suggest that the upward bias due to this reservation wage effect is, in absolute terms, at least as large or even dominates the negative bias due to classical unobserved heterogeneity.

7 Conclusions

Based on detailed longitudinal Belgian data, we estimated a Dynamic Discrete Choice model to investigate the relationship between educational attainment, overeducation, and wages. We relied on the literature on dynamic treatment effects and estimated a sequential dynamic model of educational choices and labour market outcomes (Heckman and Navarro, 2017; Heckman et al., 2016, 2018a, 2018b). This allowed us to contribute in three main ways to the literature. First, we contribute to the discussion about whether the relationships between educational attainment, overeducation and wages are truly causal. Second, we implemented a new decomposition approach, which allowed us to investigate the relationship between overeducation and the unconditional wage return to education in a more comprehensive way. Third, we explored whether overeducation is a channel that may generate both heterogeneous expected and heterogeneous realized returns to education.

With respect to our first contribution, our results suggested that being overeducated at the start of one's first job generates a significantly negative wage penalty. At age 23, this penalty was estimated to range from about 3% among those with a higher secondary or a lower tertiary education degree to about 11% among those with a higher tertiary degree. Overall, this confirms the findings of a quite extensive literature on this topic (Hartog, 2000; McGuinness, 2006; Leuven and Oosterbeek, 2011; Barnichon and Zilberberg, 2019). However, most of these earlier studies either relied on standard regression analysis or accounted for endogeneity based on identification strategies that have been strongly criticized (Leuven and Oosterbeek, 2011). By modeling overeducation as a function of all relevant past educational choices and by using the panel data structure of the data to estimate the unobserved heterogeneity component, we circumvented these problems. Interestingly, we also found this wage penalty to overeducation in the first job to persist up until age 29. This is consistent with several other studies that found overeducation to be strongly persistent (Baert et al., 2013; Meroni and Vera-Toscano, 2017; Barnichon and Zylberberg, 2019) or overeducated workers to experience no more wage growth than adequately educated workers (Büchel and Mertens, 2006; Korpi and Tåhlin, 2019). Moreover, it is also consistent with the findings of a more general literature on scarring effects of graduating in a recession or experiencing a bad labour market entry (Gregg, 2001; Oreopoulos et al., 2012, Cockx and Ghirelli, 2016).

Nevertheless, our results on our newly developed decomposition approach also revealed this overeducation penalty to generate a somehow misleading picture regarding the importance of overeducation in explaining the unconditional average wage return to education. This is due to this unconditional return being affected by the change in overeducation penalty and overeducation risk when investing in more education rather than by the level of the overeducation penalty and risk per se. In fact, with respect to obtaining a Bachelor's degree, we even found some evidence that the unconditional average wage return to education exceeds the return that would have been realized in the absence of a mismatch. This is mainly due to our finding that obtaining a Bachelor's degree (relative to obtaining a high school degree only) may be rather a way to reduce one's risk of overeducation. Moreover, also for Master's degrees, the impact of overeducation on its unconditional return seemed to be moderate at best. Though we found Master's degrees to be associated with a reduced match quality in the first job relative to Bachelor's degrees (but not relative to high school degrees), their unconditional average wage return was still estimated to be substantial. For instance, at age 29, we found their unconditional average return to be equal to about 10% relative to a return of about 12% if there were no change in match quality. The unconditional average return to obtaining a high school degree, meanwhile, was found to be much more limited, among other things due to the increased overeducation risk and penalty that is associated with obtaining such a degree relative to having obtained a lower secondary education degree only. Overall, these findings do not suggest overeducation to be indicative of considerable overinvestments in higher education. Instead, they are consistent with a polarized labour market (cf. Autor et al., 2003; Goos et al., 2009), in which obtaining a higher education degree may rather be a way to avoid overeducation.

Even if the impact of overeducation on the average unconditional wage return of obtaining a higher education degree is moderate or even positive, this does not mean that obtaining such a degree is an efficient strategy for all individuals. Indeed, in line with several other studies (e.g. Arcidiacono, 2004; Rodriguez et al., 2016), we found the between-individual heterogeneity in this unconditional return to be substantial. And we also found these unconditional returns to be smaller among those individuals that face a higher overeducation risk. Nonetheless, this heterogeneity in unconditional wage returns turned out to be fairly similar to the heterogeneity in wage returns conditional on perfect matching. Overall, this suggests that, while differences in overeducation probabilities may reflect differences in unconditional wage returns across individuals, overeducation in itself is not a channel that further enforces this heterogeneity. Indeed, even if individuals have a higher likelihood of being overeducated, obtaining a college degree may still improve their chances to obtain a medium-skilled job (cf. Verhaest et al., 2018) and, henceforth, generate a substantial wage return for these individuals. As an explanation for heterogeneous realized (ex-post) returns to education, meanwhile, overeducation was found to be much more important. By simulating the matching process based on the parameter estimates of our model, we found these realized ex-post wage returns to be negative for a substantial part of the graduates despite their ex-ante return being positive. Overall, this is consistent with overeducation being much more indicative of labour market frictions (cf. Gautier, 2002; Dolado et al., 2009) and, henceforth, investing in higher education being a risky venture (cf. Leuven and Oosterbeek, 2011).

These results have important policy implications. First of all, they suggest that reducing investments in higher education may not be the appropriate answer to observations of widespread overeducation among young workers. On the contrary, widening access to Bachelor's degree programs may even be beneficial in this respect. Second, rather than considering overeducation as being indicative of inefficient educational policies, our findings suggest it to be much more fruitful to focus on labour market policies that reduce frictions. The reduction of these frictions may not only reduce one's risk to be overeducated at the initial stage of one's career, but also minimize the scarring effects that result from this initial labour market mismatch.

We end by indicating some directions for further research. First, our analysis was based on data covering the early nineties and the first years of the new century. Not only is this a period for which job polarization has been well documented (Goos et al., 2009), but participation in higher education has only continued to increase since then. An analysis relying on more recent data would therefore be interesting. Second, the Belgian labour market is known to be quite rigid. Besides being associated with stronger overeducation penalties (Levels et al., 2014), the context of a rigid labour market is also presumed to be associated with stronger scarring effects in the case of a bad labour market entry (Cockx and Ghirelli, 2016). Estimating a similar model as ours while relying on data from a more flexible labour market context would therefore be another interesting avenue for further research. Finally, by focusing on obtaining a higher level of education, we only accounted for the quantitative dimension of additional investments in education. Several studies have shown overeducation to be correlated with the selectivity and prestige of the study programmes and institutions (Robst, 1995; Verhaest and van der Velden, 2013). It would therefore be interesting to extend our model by also accounting for this more qualitative dimension of investments in education.

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A Data

Table A1: Missing values breakdown

Total number of individuals in SONAR	**9000**
Individuals with > 2 years delay prior to primary education	76
Individuals in special needs schools	124
Inconsistent, erroneous or incomplete data on exogenous variables and educational career	638
Final sample educational outcomes	**8162**
No information on first job	701
No information on overeducation	250
Final sample overeducation start first job	**7211**
Still in education or no job at age 23	1519
Surveyed, but no wage questions at age 23	1145
Non-response or outliers wage age 23	333
Final sample wages at age 23	**4214**
Not surveyed at age 26	3686
Still in education or no job at age 26	84
Surveyed, but no wage questions at age 26	79
Non-response or outliers wage age 26	116
Final sample wages at age 26	**3246**
Not surveyed at age 29	4030
Still in education or no job at age 29	42
Surveyed, but no wage questions at age 29	45
Non-response or outliers wage age 29	38
Final sample wages at age 29	**3056**

B Treatment effects tables

Table A1: Wage returns treatment effects: Direct effects

		Direct effects											
		ATE†			ATE			ATT			ATNT		
		HSE	LTE	HTE	HSE	LTE	HTE	HSE	LTE	HTE	HSE	LTE	HTE
Wage 23	AM-AM	0.047*	0.067***	0.103***	0.034	0.074***	0.103***	0.034	0.073***	0.123***	0.031	0.074***	0.090***
		(0.027)	(0.012)	(0.020)	(0.021)	(0.011)	(0.018)	(0.021)	(0.014)	(0.017)	(0.022)	(0.011)	(0.021)
	AM-OE	0.014	0.038**	-0.010	0.001	0.045***	-0.010	0.001	0.044***	0.010	-0.002	0.045***	-0.022
		(0.027)	(0.015)	(0.024)	(0.021)	(0.014)	(0.023)	(0.021)	(0.017)	(0.024)	(0.022)	(0.014)	(0.024)
	OE-AM	0.042	0.100***	0.132***	0.028	0.106***	0.132***	0.028	0.106***	0.151***	0.025	0.107***	0.119***
		(0.032)	(0.012)	(0.023)	(0.026)	(0.011)	(0.021)	(0.026)	(0.014)	(0.020)	(0.027)	(0.010)	(0.024)
	OE-OE	0.009	0.071***	0.019	-0.005	0.078***	0.019	-0.005	0.077***	0.039	-0.008	0.078***	0.006
		(0.032)	(0.015)	(0.026)	(0.026)	(0.014)	(0.024)	(0.026)	(0.017)	(0.025)	(0.026)	(0.014)	(0.026)
	Unconditional WR	0.029	0.077***	0.063***	0.015	0.083***	0.066***	0.015	0.083***	0.091***	0.012	0.083***	0.050***
		(0.027)	(0.011)	(0.018)	(0.020)	(0.010)	(0.015)	(0.020)	(0.013)	(0.015)	(0.021)	(0.009)	(0.018)
	Unconditional WR (Dir.)	0.029	0.077***	0.063***	0.015	0.083***	0.066***	0.015	0.083***	0.091***	0.012	0.083***	0.050***
		(0.027)	(0.011)	(0.018)	(0.020)	(0.010)	(0.015)	(0.020)	(0.013)	(0.015)	(0.021)	(0.009)	(0.018)
Wage 26	AM-AM	0.073**	0.087***	0.119***	0.072***	0.092***	0.126***	0.073***	0.085***	0.138***	0.067**	0.099***	0.116***
		(0.033)	(0.012)	(0.014)	(0.026)	(0.011)	(0.013)	(0.026)	(0.014)	(0.013)	(0.028)	(0.010)	(0.015)
	AM-OE	0.057*	0.051***	0.048***	0.057**	0.056***	0.054***	0.057**	0.049***	0.067***	0.051*	0.064***	0.045**
		(0.033)	(0.015)	(0.017)	(0.026)	(0.014)	(0.017)	(0.026)	(0.017)	(0.019)	(0.028)	(0.014)	(0.018)
	OE-AM	0.014	0.103***	0.155***	0.013	0.108***	0.161***	0.014	0.101***	0.174***	0.008	0.115***	0.152***
		(0.038)	(0.012)	(0.017)	(0.032)	(0.011)	(0.016)	(0.032)	(0.014)	(0.016)	(0.034)	(0.010)	(0.018)
	OE-OE	-0.002	0.067***	0.084***	-0.002	0.072***	0.090***	-0.002	0.065***	0.103***	-0.008	0.080***	0.080***
		(0.038)	(0.015)	(0.019)	(0.032)	(0.014)	(0.019)	(0.032)	(0.017)	(0.021)	(0.034)	(0.014)	(0.020)
	Unconditional WR	0.051	0.087***	0.101***	0.050**	0.091***	0.109***	0.050**	0.085***	0.125***	0.044	0.098***	0.098***
		(0.032)	(0.011)	(0.012)	(0.025)	(0.010)	(0.011)	(0.025)	(0.013)	(0.012)	(0.027)	(0.009)	(0.013)
	Unconditional WR (Dir.)	0.051	0.087***	0.101***	0.050**	0.091***	0.109***	0.050**	0.085***	0.125***	0.044	0.098***	0.098***
		(0.032)	(0.011)	(0.012)	(0.025)	(0.010)	(0.011)	(0.025)	(0.013)	(0.012)	(0.027)	(0.009)	(0.013)
Wage 29	AM-AM	0.044	0.053***	0.112***	0.017	0.064***	0.121***	0.018	0.041***	0.137***	0.014	0.087***	0.110***
		(0.033)	(0.012)	(0.012)	(0.026)	(0.011)	(0.011)	(0.026)	(0.015)	(0.012)	(0.028)	(0.009)	(0.012)
	AM-OE	0.008	0.018	0.027**	-0.019	0.028**	0.037***	-0.019	0.006	0.053***	-0.022	0.052***	0.025*
		(0.033)	(0.015)	(0.013)	(0.026)	(0.014)	(0.013)	(0.026)	(0.017)	(0.014)	(0.028)	(0.013)	(0.014)
	OE-AM	0.069*	0.090***	0.147***	0.042	0.100***	0.157***	0.042	0.078***	0.173***	0.039	0.124***	0.145***
		(0.037)	(0.013)	(0.014)	(0.030)	(0.011)	(0.014)	(0.030)	(0.016)	(0.014)	(0.031)	(0.010)	(0.015)
	OE-OE	0.032	0.054***	0.063***	0.005	0.065***	0.072***	0.005	0.043**	0.089***	0.002	0.088***	0.061***
		(0.036)	(0.015)	(0.015)	(0.029)	(0.014)	(0.014)	(0.029)	(0.018)	(0.015)	(0.030)	(0.013)	(0.015)
	Unconditional WR	0.033	0.063***	0.088***	0.006	0.074***	0.099***	0.006	0.052***	0.119***	0.003	0.096***	0.085***
		(0.032)	(0.011)	(0.010)	(0.024)	(0.010)	(0.009)	(0.024)	(0.015)	(0.010)	(0.026)	(0.008)	(0.011)
	Unconditional WR (Dir.)	0.033	0.063***	0.088***	0.006	0.074***	0.099***	0.006	0.052***	0.119***	0.003	0.096***	0.085***
		(0.032)	(0.011)	(0.010)	(0.024)	(0.010)	(0.009)	(0.024)	(0.015)	(0.010)	(0.026)	(0.008)	(0.011)

Notes: we simplify the notation and we refer to: (i) Wage returns AM-AM as $\Omega^{M,M}_{a,j}$, (ii) Wage returns AM-OE as $\Omega^{M,O}_{a,j}$, (iii) Wage returns OE-AM as $\Omega^{O,M}_{a,j}$ and (iv) Wage returns OE-OE as $\Omega^{O,O}_{a,j}$. Moreover, Unconditional WR refers to Unconditional Wage Returns and Unconditional WR (Dir.) refers to the Unconditional Wage Return computed as the direct effect.

Table A2: Wage returns treatment effects: Total effects

		Total effects											
		ATE†			ATE			ATT			ATNT		
		HSE	LTE	HTE	HSE	LTE	HTE	HSE	LTE	HTE	HSE	LTE	HTE
Wage 23	AM-AM	0.094***	0.093***	0.103***	0.038*	0.079***	0.103***	0.037*	0.073***	0.123***	0.051**	0.086***	0.090***
		(0.025)	(0.012)	(0.020)	(0.021)	(0.011)	(0.018)	(0.021)	(0.014)	(0.017)	(0.022)	(0.011)	(0.021)
	AM-OE	0.052**	0.048***	-0.010	0.004	0.047***	-0.010	0.003	0.044***	0.010	0.017	0.049***	-0.022
		(0.026)	(0.014)	(0.024)	(0.021)	(0.014)	(0.023)	(0.021)	(0.017)	(0.024)	(0.022)	(0.013)	(0.024)
	OE-AM	0.089***	0.126***	0.132***	0.032	0.112***	0.132***	0.031	0.106***	0.151***	0.046*	0.118***	0.119***
		(0.030)	(0.012)	(0.023)	(0.026)	(0.011)	(0.021)	(0.026)	(0.014)	(0.020)	(0.027)	(0.010)	(0.024)
	OE-OE	0.047	0.081***	0.019	-0.001	0.080***	0.019	-0.002	0.077***	0.039	0.011	0.082***	0.006
		(0.030)	(0.014)	(0.026)	(0.026)	(0.014)	(0.024)	(0.026)	(0.017)	(0.025)	(0.027)	(0.013)	(0.026)
	Unconditional WR	0.077***	0.096***	0.063***	0.019	0.087***	0.066***	0.018	0.083***	0.091***	0.033	0.091***	0.050***
		(0.025)	(0.011)	(0.018)	(0.020)	(0.010)	(0.015)	(0.020)	(0.013)	(0.015)	(0.022)	(0.009)	(0.018)
	Unconditional WR (Dir.)	0.029	0.077***	0.063***	0.015	0.083***	0.066***	0.015	0.083***	0.091***	0.012	0.083***	0.050***
		(0.027)	(0.011)	(0.018)	(0.020)	(0.010)	(0.015)	(0.020)	(0.013)	(0.015)	(0.021)	(0.009)	(0.018)
Wage 26	AM-AM	0.147***	0.127***	0.119***	0.080***	0.101***	0.126***	0.078***	0.085***	0.138***	0.097***	0.117***	0.116***
		(0.031)	(0.011)	(0.014)	(0.026)	(0.011)	(0.013)	(0.026)	(0.014)	(0.013)	(0.029)	(0.010)	(0.015)
	AM-OE	0.113***	0.081***	0.048***	0.062**	0.063***	0.054***	0.061**	0.049***	0.067***	0.075**	0.077***	0.045**
		(0.032)	(0.014)	(0.017)	(0.026)	(0.014)	(0.017)	(0.026)	(0.017)	(0.019)	(0.029)	(0.013)	(0.018)
	OE-AM	0.088**	0.143***	0.155***	0.020	0.116***	0.161***	0.019	0.101***	0.174***	0.038	0.133***	0.152***
		(0.036)	(0.012)	(0.017)	(0.032)	(0.011)	(0.016)	(0.032)	(0.014)	(0.016)	(0.034)	(0.010)	(0.018)
	OE-OE	0.053	0.097***	0.084***	0.003	0.079***	0.090***	0.002	0.065***	0.103***	0.016	0.093***	0.080***
		(0.036)	(0.014)	(0.019)	(0.032)	(0.014)	(0.019)	(0.032)	(0.017)	(0.021)	(0.034)	(0.013)	(0.020)
	Unconditional WR	0.122***	0.122***	0.101***	0.057**	0.099***	0.109***	0.056**	0.085***	0.125***	0.073**	0.114***	0.098***
		(0.031)	(0.011)	(0.012)	(0.025)	(0.010)	(0.011)	(0.025)	(0.013)	(0.012)	(0.029)	(0.009)	(0.013)
	Unconditional WR (Dir.)	0.051	0.087***	0.101***	0.050**	0.091***	0.109***	0.050**	0.085***	0.125***	0.044	0.098***	0.098***
		(0.032)	(0.011)	(0.012)	(0.025)	(0.010)	(0.011)	(0.025)	(0.013)	(0.012)	(0.027)	(0.009)	(0.013)
Wage 29	AM-AM	0.086***	0.096***	0.112***	0.020	0.073***	0.121***	0.018	0.041***	0.137***	0.040	0.106***	0.110***
		(0.031)	(0.012)	(0.012)	(0.026)	(0.011)	(0.011)	(0.026)	(0.015)	(0.012)	(0.028)	(0.009)	(0.012)
	AM-OE	0.040	0.047***	0.027**	-0.017	0.034**	0.037***	-0.019	0.006	0.053***	0.001	0.064***	0.025*
		(0.031)	(0.014)	(0.013)	(0.026)	(0.013)	(0.013)	(0.026)	(0.017)	(0.014)	(0.027)	(0.012)	(0.014)
	OE-AM	0.111***	0.133***	0.147***	0.044	0.110***	0.157***	0.043	0.078***	0.173***	0.064**	0.142***	0.145***
		(0.034)	(0.012)	(0.014)	(0.029)	(0.011)	(0.014)	(0.029)	(0.016)	(0.014)	(0.031)	(0.010)	(0.015)
	OE-OE	0.064*	0.084***	0.063***	0.007	0.071***	0.072***	0.005	0.043**	0.089***	0.026	0.100***	0.061***
		(0.034)	(0.014)	(0.015)	(0.029)	(0.014)	(0.014)	(0.029)	(0.018)	(0.015)	(0.030)	(0.012)	(0.015)
	Unconditional WR	0.077***	0.101***	0.088***	0.008	0.081***	0.099***	0.007	0.052***	0.119***	0.029	0.112***	0.085***
		(0.030)	(0.011)	(0.010)	(0.024)	(0.010)	(0.009)	(0.024)	(0.015)	(0.010)	(0.026)	(0.008)	(0.011)
	Unconditional WR (Dir.)	0.033	0.063***	0.088***	0.006	0.074***	0.099***	0.006	0.052***	0.119***	0.003	0.096***	0.085***
		(0.032)	(0.011)	(0.010)	(0.024)	(0.010)	(0.009)	(0.024)	(0.015)	(0.010)	(0.026)	(0.008)	(0.011)

Notes: we simplify the notation and we refer to: (i) Wage returns AM-AM as $\Omega^{M,M}_{a,j}$, (ii) Wage returns AM-OE as $\Omega^{M,O}_{a,j}$, (iii) Wage returns OE-AM as $\Omega^{O,M}_{a,j}$ and (iv) Wage returns OE-OE as $\Omega^{O,O}_{a,j}$. Moreover, Unconditional WR refers to Unconditional Wage Returns and Unconditional WR (Dir.) refers to the Unconditional Wage Return computed as the direct effect.

Table A3: Overeducation wage penalty

	Direct effects											
		ATE†			ATE			ATT			ATNT	
	Wage 23	Wage 26	Wage 29	Wage 23	Wage 26	Wage 29	Wage 23	Wage 26	Wage 29	Wage 23	Wage 26	Wage 29
HSE	-0.033***	-0.016*	-0.037***	-0.033***	-0.016*	-0.037***	-0.033***	-0.016*	-0.037***	-0.033***	-0.016	-0.037***
	(0.008)	(0.009)	(0.009)	(0.008)	(0.009)	(0.009)	(0.008)	(0.009)	(0.009)	(0.008)	(0.011)	(0.010)
LTE	-0.029**	-0.035***	-0.035***	-0.029**	-0.035***	-0.035***	-0.029**	-0.036***	-0.035***	-0.029**	-0.035***	-0.036***
	(0.013)	(0.013)	(0.011)	(0.013)	(0.013)	(0.011)	(0.013)	(0.013)	(0.011)	(0.013)	(0.013)	(0.011)
HTE	-0.113***	-0.071***	-0.084***	-0.113***	-0.071***	-0.084***	-0.113***	-0.071***	-0.084***	-0.113***	-0.071***	-0.084***
	(0.026)	(0.019)	(0.013)	(0.026)	(0.019)	(0.013)	(0.026)	(0.019)	(0.013)	(0.026)	(0.019)	(0.013)

	Total effects											
		ATE†			ATE			ATT			ATNT	
	Wage 23	Wage 26	Wage 29	Wage 23	Wage 26	Wage 29	Wage 23	Wage 26	Wage 29	Wage 23	Wage 26	Wage 29
HSE	-0.042***	-0.034***	-0.047***	-0.033***	-0.017**	-0.037***	-0.033***	-0.017**	-0.037***	-0.034***	-0.022**	-0.039***
	(0.007)	(0.007)	(0.006)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.007)	(0.010)	(0.008)
LTE	-0.045***	-0.046***	-0.049***	-0.032***	-0.038***	-0.039***	-0.029**	-0.036***	-0.035***	-0.036***	-0.040***	-0.042***
	(0.012)	(0.011)	(0.009)	(0.012)	(0.012)	(0.011)	(0.013)	(0.013)	(0.011)	(0.012)	(0.011)	(0.010)
HTE	-0.113***	-0.071***	-0.084***	-0.113***	-0.071***	-0.084***	-0.113***	-0.071***	-0.084***	-0.113***	-0.071***	-0.084***
	(0.026)	(0.019)	(0.013)	(0.026)	(0.019)	(0.013)	(0.026)	(0.019)	(0.013)	(0.026)	(0.019)	(0.013)

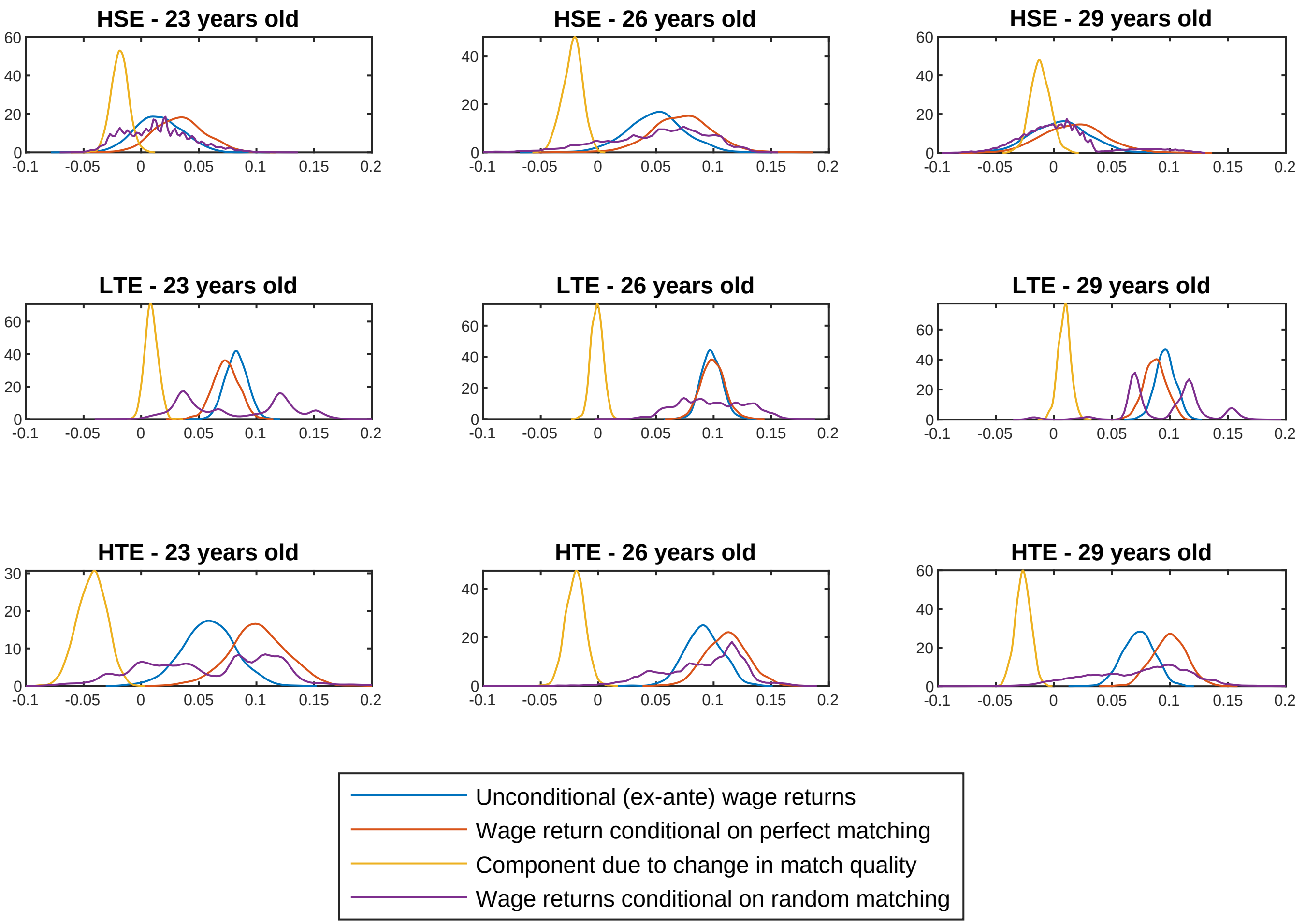
Table A4: Decomposition wage returns

		Direct effects						Total effects					
		ATE† HSE	LTE	HTE	ATE HSE	LTE	HTE	ATE† HSE	LTE	HTE	ATE HSE	LTE	HTE
Wage 23	Unconditional WR	0.029	0.077***	0.063***	0.015	0.083***	0.066***	0.077***	0.096***	0.063***	0.019	0.087***	0.066***
		(0.027)	(0.011)	(0.018)	(0.020)	(0.010)	(0.015)	(0.025)	(0.011)	(0.018)	(0.020)	(0.010)	(0.015)
	AM-AM	0.047*	0.067***	0.103***	0.034	0.074***	0.103***	0.094***	0.093***	0.103***	0.038*	0.079***	0.103***
		(0.027)	(0.012)	(0.020)	(0.021)	(0.011)	(0.018)	(0.025)	(0.012)	(0.020)	(0.021)	(0.011)	(0.018)
	Difference	-0.018**	0.010*	-0.040***	-0.019**	0.010*	-0.037***	-0.017***	0.003	-0.040***	-0.018**	0.008	-0.037***
		(0.007)	(0.006)	(0.012)	(0.007)	(0.006)	(0.011)	(0.007)	(0.006)	(0.012)	(0.007)	(0.006)	(0.011)
	Change in match quality	-0.019**	0.010*	-0.040***	-0.018**	0.009*	-0.036***	-0.017***	0.002	-0.040***	-0.018**	0.007	-0.036***
		(0.007)	(0.006)	(0.012)	(0.007)	(0.005)	(0.011)	(0.007)	(0.003)	(0.012)	(0.007)	(0.005)	(0.011)
	Change in overeducation penalty	-0.011	0.002	-0.022***	-0.011	0.002	-0.022***	-0.013*	-0.001	-0.022***	-0.011	0.000	-0.022***
		(0.007)	(0.008)	(0.007)	(0.007)	(0.008)	(0.008)	(0.007)	(0.003)	(0.007)	(0.007)	(0.007)	(0.008)
	Change in overeducation risk	-0.008***	0.008**	-0.018***	-0.008**	0.007**	-0.014***	-0.004	0.003***	-0.018***	-0.007**	0.007**	-0.014***
		(0.003)	(0.003)	(0.005)	(0.003)	(0.003)	(0.004)	(0.003)	(0.001)	(0.005)	(0.003)	(0.003)	(0.004)
Wage 26	Unconditional WR	0.051	0.087***	0.101***	0.050**	0.091***	0.109***	0.122***	0.122***	0.101***	0.057**	0.099***	0.109***
		(0.032)	(0.011)	(0.012)	(0.025)	(0.010)	(0.011)	(0.031)	(0.011)	(0.012)	(0.025)	(0.010)	(0.011)
	AM-AM	0.073**	0.087***	0.119***	0.072***	0.092***	0.126***	0.147***	0.127***	0.119***	0.080***	0.101***	0.126***
		(0.033)	(0.012)	(0.014)	(0.026)	(0.011)	(0.013)	(0.031)	(0.011)	(0.014)	(0.026)	(0.011)	(0.013)
	Diff	-0.022**	-0.000	-0.018**	-0.022***	-0.001	-0.016**	-0.025***	-0.004	-0.018**	-0.023***	-0.002	-0.016**
		(0.009)	(0.005)	(0.007)	(0.009)	(0.005)	(0.007)	(0.008)	(0.005)	(0.007)	(0.008)	(0.005)	(0.007)
	Change in match quality	-0.022**	-0.000	-0.018**	-0.022***	-0.001	-0.016**	-0.025***	-0.002	-0.018**	-0.023***	-0.002	-0.016**
		(0.009)	(0.005)	(0.007)	(0.008)	(0.005)	(0.007)	(0.008)	(0.002)	(0.007)	(0.008)	(0.005)	(0.007)
	Change in overeducation penalty	-0.019**	-0.009	-0.008	-0.019**	-0.015	-0.008	-0.023***	-0.003*	-0.008	-0.019**	-0.009	-0.008
		(0.008)	(0.016)	(0.006)	(0.008)	(0.017)	(0.006)	(0.009)	(0.002)	(0.006)	(0.008)	(0.023)	(0.006)
	Change in overeducation risk	-0.004	0.009	-0.010***	-0.003	0.014	-0.008**	-0.002	0.001	-0.010***	-0.003	0.008	-0.008**
		(0.003)	(0.015)	(0.004)	(0.002)	(0.017)	(0.004)	(0.003)	(0.001)	(0.004)	(0.002)	(0.023)	(0.004)
Wage 29	Unconditional WR	0.033	0.063***	0.088***	0.006	0.074***	0.099***	0.077***	0.101***	0.088***	0.008	0.081***	0.099***
		(0.032)	(0.011)	(0.010)	(0.024)	(0.010)	(0.009)	(0.030)	(0.011)	(0.010)	(0.024)	(0.010)	(0.009)
	AM-AM	0.044	0.053***	0.112***	0.017	0.064***	0.121***	0.086***	0.096***	0.112***	0.020	0.073***	0.121***
		(0.033)	(0.012)	(0.012)	(0.026)	(0.011)	(0.011)	(0.031)	(0.012)	(0.012)	(0.026)	(0.011)	(0.011)
	Diff	-0.012	0.010*	-0.024***	-0.012	0.010*	-0.022***	-0.010	0.004	-0.024***	-0.011	0.008	-0.022***
		(0.008)	(0.005)	(0.006)	(0.008)	(0.005)	(0.006)	(0.007)	(0.005)	(0.006)	(0.008)	(0.005)	(0.006)
	Change in match quality	-0.012	0.010*	-0.024***	-0.012	0.009*	-0.022***	-0.010	0.002	-0.024***	-0.011	0.008	-0.022***
		(0.008)	(0.005)	(0.006)	(0.008)	(0.005)	(0.006)	(0.007)	(0.002)	(0.006)	(0.008)	(0.005)	(0.006)
	Change in overeducation penalty	-0.003	0.001	-0.012***	-0.003	0.001	-0.012***	-0.006	-0.001	-0.012***	-0.003	-0.001	-0.012***
		(0.008)	(0.007)	(0.004)	(0.009)	(0.007)	(0.004)	(0.008)	(0.002)	(0.004)	(0.009)	(0.006)	(0.004)
	Change in overeducation risk	-0.009**	0.009***	-0.012***	-0.008	0.009***	-0.010***	-0.004	0.003***	-0.012***	-0.008	0.008***	-0.010***
		(0.004)	(0.003)	(0.003)	(0.005)	(0.003)	(0.003)	(0.004)	(0.001)	(0.003)	(0.005)	(0.003)	(0.003)

Notes: The measures used in the decomposition are the following: unconditional (ex-ante) wage returns (Unconditional WR), wage return conditional on perfect matching (WR conditional on PM).

B.1 Decomposition of change in match quality graphs

Figure B1: Decomposition of change in match quality



C Model estimates

Table C1: Model estimates

		BM - K3		
			S.E.	p
	Female	-0.006	0.182	0.975
	Siblings	0.059	0.052	0.256
	Foreign origin	1.551	0.268	0.000
	Education Father	-0.008	0.034	0.808
	Education Mother	0.014	0.031	0.655
Delay	Birth day / 100	0.443	0.094	0.000
Primary Education	Unemployment Delay	0.023	0.032	0.478
	Cohort 1978	-0.010	0.275	0.972
	Cohort 1980	0.294	0.246	0.232
	_cons	-5.473	0.524	0.000
	Het par 1	-0.481	0.194	0.013
	Het par 2	-0.161	0.360	0.655
	Female	-0.274	0.079	0.001
	Siblings	0.094	0.025	0.000
	Foreign origin	0.822	0.135	0.000
	Education Father	-0.113	0.015	0.000
	Education Mother	-0.070	0.014	0.000
Delay	Birth day / 100	0.298	0.040	0.000
Secondary	Unemployment Delay	-0.001	0.020	0.969
Education	Delay	3.048	0.215	0.000
	Cohort 1978	0.258	0.120	0.031
	Cohort 1980	0.236	0.114	0.038
	_cons	-1.927	0.268	0.000
	Het par 1	-0.358	0.085	0.000
	Het par 2	-0.340	0.172	0.048

Table C1: Model estimates

	Female	0.410	0.050	0.000
	Siblings	-0.087	0.019	0.000
	Foreign origin	0.171	0.125	0.171
	Education Father	0.125	0.009	0.000
	Education Mother	0.145	0.008	0.000
Start	Birth day / 100	-0.077	0.025	0.002
and track choice	Unemployment Delay	-0.025	0.011	0.027
Secondary	Delay	0.960	0.224	0.000
Education	Delay SE	-1.975	0.109	0.000
3rd year	Cohort 1978	-0.168	0.070	0.017
	Cohort 1980	-0.287	0.079	0.000
	Het par 1	0.423	0.057	0.000
	Het par 2	0.190	0.108	0.078
	cut 1	-4.295	0.181	0.000
	cut 2	1.174	0.130	0.000
	Female	0.660	0.130	0.000
	Siblings	-0.114	0.034	0.001
	Foreign origin	-0.037	0.211	0.862
	Education Father	0.068	0.025	0.008
	Education Mother	0.116	0.025	0.000
	Birth day / 100	0.004	0.062	0.946
Lower	Unemployment Delay	-0.038	0.028	0.183
Secondary	Delay	-0.420	0.339	0.215
Education	Delay SE	-0.713	0.144	0.000
	Track Choice LSE	1.905	0.219	0.000
	Cohort 1978	0.198	0.190	0.299
	Cohort 1980	0.141	0.178	0.429
	_cons	2.011	0.326	0.000
	Het par 1	0.418	0.131	0.001
	Het par 2	0.016	0.233	0.944

Table C1: Model estimates

Start and track choice Secondary Education 5th year	Female	0.347	0.076	0.000
	Siblings	-0.039	0.029	0.179
	Foreign origin	-0.072	0.185	0.696
	Education Father	0.070	0.014	0.000
	Education Mother	0.065	0.013	0.000
	Birth day / 100	0.018	0.038	0.644
	Unemployment Delay	-0.057	0.018	0.001
	Delay	-0.348	0.285	0.222
	Delay SE	-0.591	0.156	0.000
	Track Choice LSE	6.115	0.181	0.000
	Cohort 1978	0.244	0.097	0.012
	Cohort 1980	0.104	0.094	0.269
	Het par 1	0.389	0.086	0.000
	Het par 2	0.181	0.162	0.263
	cut 1	-2.978	0.248	0.000
	cut 2	5.218	0.292	0.000
Higher Secondary Education	Female	0.706	0.111	0.000
	Siblings	-0.081	0.033	0.015
	Foreign origin	-0.600	0.190	0.002
	Education Father	0.046	0.020	0.025
	Education Mother	0.065	0.020	0.001
	Birth day / 100	0.115	0.053	0.030
	Unemployment Delay	-0.035	0.024	0.144
	Delay	-0.266	0.340	0.434
	Delay SE	-0.594	0.139	0.000
	Track Choice LSE	0.147	0.177	0.407
	Track Choice HSE	1.311	0.217	0.000
	Cohort 1978	-0.161	0.139	0.248
	Cohort 1980	-0.157	0.133	0.240
	_cons	1.707	0.319	0.000
	Het par 1	0.727	0.111	0.000

Table C1: Model estimates

	Het par 2	0.302	0.209	0.149
	Female	0.129	0.049	0.008
	Siblings	-0.036	0.020	0.079
	Foreign origin	-0.120	0.140	0.391
	Education Father	0.062	0.009	0.000
	Education Mother	0.090	0.008	0.000
	Birth day / 100	0.021	0.025	0.391
Start	Unemployment Delay	-0.009	0.011	0.404
and track choice	Delay	0.404	0.231	0.080
Lower	Delay SE	-0.721	0.105	0.000
Tertiary	Track Choice LSE	1.285	0.095	0.000
Education	Track Choice HSE	2.238	0.106	0.000
	Cohort 1978	0.150	0.071	0.035
	Cohort 1980	0.156	0.069	0.024
	Het par 1	0.494	0.058	0.000
	Het par 2	0.032	0.109	0.767
	cut 1	1.354	0.136	0.000
	cut 2	5.212	0.158	0.000
	Female	0.550	0.071	0.000
	Siblings	-0.015	0.030	0.625
	Foreign origin	-0.808	0.202	0.000
	Education Father	0.038	0.013	0.003
	Education Mother	0.032	0.012	0.007
	Birth day / 100	-0.007	0.036	0.845
	Unemployment Delay	-0.057	0.016	0.000
Lower	Delay	-0.257	0.323	0.426
Tertiary	Delay SE	-0.296	0.165	0.074
Education	Track Choice LSE	0.075	0.112	0.506
	Track Choice HSE	1.117	0.112	0.000
	Track Choice LTE	0.650	0.098	0.000
	Cohort 1978	0.382	0.106	0.000
	Cohort 1980	0.259	0.102	0.011

Table C1: Model estimates

	_cons	-0.352	0.200	0.079
	Het par 1	0.581	0.082	0.000
	Het par 2	0.035	0.153	0.817
Start and track choice Higher Tertiary Education	Female	-0.518	0.076	0.000
	Siblings	-0.025	0.036	0.490
	Foreign origin	0.147	0.288	0.609
	Education Father	0.051	0.013	0.000
	Education Mother	0.049	0.012	0.000
	Birth day / 100	0.059	0.038	0.126
	Unemployment Delay	-0.031	0.017	0.071
	Delay	0.708	0.411	0.085
	Delay SE	-0.346	0.280	0.217
	Track Choice LSE	-0.185	0.206	0.369
	Track Choice HSE	1.083	0.185	0.000
	Track Choice LTE	2.854	0.086	0.000
	Cohort 1978	0.101	0.096	0.297
	Cohort 1980	0.019	0.096	0.843
	Het par 1	0.500	0.100	0.000
	Het par 2	1.030	0.173	0.000
	cut 1	2.544	0.258	0.000
	cut 2	3.647	0.263	0.000
Higher Tertiary Education	Female	0.296	0.167	0.077
	Siblings	-0.100	0.075	0.183
	Foreign origin	-0.710	0.543	0.192
	Education Father	-0.032	0.030	0.281
	Education Mother	-0.060	0.029	0.036
	Birth day / 100	0.166	0.085	0.051
	Unemployment Delay	0.052	0.037	0.160
	Delay	-0.090	0.791	0.909
	Delay SE	-1.481	0.617	0.016
	Track Choice LSE	-0.283	0.857	0.741
	Track Choice HSE	-0.715	0.730	0.328

Table C1: Model estimates

	Track Choice LTE	-0.219	0.305	0.473
	Track Choice HTE	0.058	0.296	0.845
	Cohort 1978	0.097	0.203	0.634
	Cohort 1980	0.323	0.211	0.126
	_cons	10.302	6.187	0.096
	Het par 1	-7.334	6.144	0.233
	Het par 2	-7.825	6.149	0.203
Overeducation at the start of the career	Female	-0.061	0.054	0.258
	Siblings	0.014	0.020	0.488
	Foreign origin	0.008	0.134	0.952
	Education Father	0.000	0.010	0.959
	Education Mother	-0.046	0.009	0.000
	Birth day / 100	0.004	0.026	0.887
	Unemployment Delay	0.036	0.012	0.004
	Delay SE	0.016	0.094	0.865
	Track Choice LSE	0.089	0.576	0.877
	Start HSE	-0.569	0.251	0.023
	Track Choice HSE	0.373	0.183	0.041
	HSE	1.580	0.142	0.000
	Start LTE	0.074	0.081	0.361
	Track Choice LTE	0.062	0.117	0.598
	LTE	-1.113	0.083	0.000
	Start THE	0.426	0.446	0.339
	Track Choice HTE	-0.460	0.124	0.000
	HTE	0.362	0.438	0.408
	Cohort 1978	0.304	0.068	0.000
	Cohort 1980	0.442	0.070	0.000
	_cons	-1.336	0.280	0.000
	Het par 1	-0.156	0.061	0.010
	Het par 2	0.135	0.113	0.232

Table C1: Model estimates

	Female	0.029	0.062	0.642
	Siblings	-0.050	0.022	0.022
	Foreign origin	-0.576	0.145	0.000
	Education Father	-0.035	0.011	0.001
	Education Mother	-0.033	0.010	0.002
	Birth day / 100	-0.040	0.030	0.195
	Unemployment Delay	-0.001	0.015	0.967
	Delay SE	-0.104	0.106	0.325
	Track Choice LSE	-0.113	0.391	0.773
	LSE	-0.102	0.255	0.688
	Start HSE	0.141	0.259	0.587
Selection	Track Choice HSE	-0.200	0.209	0.338
equation wage	HSE	0.120	0.145	0.408
at 23	Start LTE	-0.369	0.097	0.000
	Track Choice LTE	-0.157	0.130	0.225
	LTE	-0.178	0.094	0.059
	Start THE	-0.846	0.543	0.119
	Track Choice HTE	-0.169	0.167	0.310
	HTE	-0.189	0.535	0.723
	Overeducation	0.050	0.067	0.452
	Cohort 1978	1.337	0.081	0.000
	Cohort 1980	1.694	0.084	0.000
	_cons	0.713	0.237	0.003
	Het par 1	-0.054	0.068	0.427
	Het par 2	0.083	0.130	0.524

Table C1: Model estimates

Log-wage at 23	Female	-0.075	0.006	0.000
	Siblings	-0.003	0.002	0.127
	Foreign origin	0.024	0.014	0.088
	Education Father	-0.001	0.001	0.405
	Education Mother	0.001	0.001	0.397
	Birth day / 100	0.000	0.003	0.924
	Unemployment Delay	0.001	0.001	0.442
	Delay SE	-0.015	0.009	0.118
	Track Choice LSE	-0.008	0.039	0.827
	LSE	0.016	0.024	0.501
	Start HSE	0.013	0.024	0.574
	Track Choice HSE	0.013	0.020	0.506
	HSE	0.013	0.014	0.338
	Start LTE	0.019	0.009	0.031
	Track Choice LTE	-0.007	0.014	0.588
	LTE	0.068	0.010	0.000
	Start THE	0.052	0.073	0.473
	Track Choice HTE	0.082	0.023	0.000
	HTE	-0.002	0.072	0.978
	Overeducation	0.007	0.022	0.736
	Overeducation*HSE	-0.040	0.023	0.080
	Overeducation*LTE	-0.001	0.015	0.971
	Overeducation*HTE	-0.071	0.027	0.010
	Cohort 1978	0.023	0.008	0.006
	Cohort 1980	0.031	0.008	0.000
	_cons	1.913	0.022	0.000
	Het par 1	-0.007	0.006	0.265
	Het par 2	0.186	0.012	0.000
	sigma	0.187	0.002	0.000

Table C1: Model estimates

Selection equation wage at 26	Female	-0.278	0.147	0.060
	Siblings	0.033	0.050	0.513
	Foreign origin	-1.322	0.283	0.000
	Education Father	0.037	0.027	0.170
	Education Mother	0.018	0.026	0.472
	Birth day / 100	-0.005	0.073	0.945
	Unemployment Delay	-0.052	0.035	0.134
	Delay SE	0.193	0.250	0.440
	Track Choice LSE	0.715	1.009	0.479
	LSE	1.036	0.717	0.148
	Start HSE	-0.199	0.748	0.790
	Track Choice HSE	0.111	0.498	0.824
	HSE	-0.627	0.387	0.105
	Start LTE	-0.297	0.217	0.171
	Track Choice LTE	-0.423	0.282	0.134
	LTE	0.136	0.218	0.532
	Start THE	-1.506	0.691	0.029
	Track Choice HTE	-0.478	0.462	0.301
	HTE	2.020	0.644	0.002
	Overeducation	-0.456	0.157	0.004
	Cohort 1978	-0.439	0.164	0.008
	_cons	-3.626	0.574	0.000
	Het par 1	6.929	0.248	0.000
	Het par 2	6.637	0.317	0.000

Table C1: Model estimates

	Female	-0.070	0.006	0.000
	Siblings	-0.003	0.002	0.116
	Foreign origin	0.036	0.016	0.027
	Education Father	0.001	0.001	0.486
	Education Mother	0.001	0.001	0.399
	Birth day / 100	-0.009	0.003	0.003
	Unemployment Delay	0.001	0.001	0.369
	Delay SE	-0.022	0.010	0.034
	Track Choice LSE	0.034	0.044	0.434
	LSE	0.018	0.027	0.510
	Start HSE	0.025	0.027	0.352
	Track Choice HSE	0.024	0.019	0.199
	HSE	0.023	0.015	0.124
Log-wage	Start LTE	0.017	0.009	0.061
at 26	Track Choice LTE	0.001	0.013	0.939
	LTE	0.085	0.010	0.000
	Start THE	-0.020	0.045	0.659
	Track Choice HTE	0.050	0.016	0.002
	HTE	0.121	0.044	0.006
	Overeducation	0.058	0.027	0.030
	Overeducation*HSE	-0.077	0.028	0.006
	Overeducation*LTE	-0.021	0.015	0.176
	Overeducation*HTE	-0.030	0.022	0.171
	Cohort 1978	0.016	0.007	0.011
	_cons	1.370	0.038	0.000
	Het par 1	0.567	0.031	0.000
	Het par 2	0.961	0.032	0.000
	sigma	0.144	0.002	0.000

Table C1: Model estimates

	Female	-0.021	0.101	0.833
	Siblings	0.049	0.035	0.162
	Foreign origin	-1.006	0.206	0.000
	Education Father	0.022	0.018	0.230
	Education Mother	0.018	0.017	0.287
	Birth day / 100	-0.086	0.051	0.090
	Unemployment Delay	-0.005	0.024	0.822
	Delay SE	-0.112	0.169	0.508
	Track Choice LSE	0.557	0.737	0.450
	LSE	0.362	0.427	0.396
	Start HSE	0.027	0.440	0.951
Selection equation wage at 29	Track Choice HSE	0.108	0.375	0.775
	HSE	0.009	0.243	0.970
	Start LTE	-0.254	0.157	0.106
	Track Choice LTE	0.347	0.229	0.129
	LTE	0.299	0.155	0.053
	Start THE	-0.575	0.686	0.402
	Track Choice HTE	-0.168	0.266	0.528
	HTE	0.911	0.674	0.176
	Overeducation	-0.052	0.109	0.636
	Cohort 1978	1.018	0.106	0.000
	_cons	-4.575	0.378	0.000
	Het par 1	5.600	0.181	0.000
	Het par 2	5.264	0.229	0.000

Table C1: Model estimates

	Female	-0.060	0.006	0.000
	Siblings	-0.003	0.002	0.184
	Foreign origin	0.033	0.014	0.019
	Education Father	0.000	0.001	0.899
	Education Mother	0.000	0.001	0.713
	Birth day / 100	-0.001	0.003	0.660
	Unemployment Delay	0.000	0.001	0.722
	Delay SE	-0.024	0.010	0.019
	Track Choice LSE	0.011	0.041	0.779
	LSE	0.022	0.028	0.424
	Start HSE	-0.053	0.028	0.053
	Track Choice HSE	0.091	0.022	0.000
	HSE	0.052	0.015	0.001
Log-wage	Start LTE	0.013	0.009	0.155
at 29	Track Choice LTE	0.004	0.011	0.751
	LTE	0.076	0.010	0.000
	Start THE	0.116	0.045	0.010
	Track Choice HTE	0.042	0.012	0.001
	HTE	-0.010	0.045	0.827
	Overeducation	-0.028	0.025	0.258
	Overeducation*HSE	-0.009	0.027	0.738
	Overeducation*LTE	-0.001	0.014	0.928
	Overeducation*HTE	-0.047	0.017	0.005
	Cohort 1978	0.030	0.006	0.000
	_cons	1.476	0.031	0.000
	Het par 1	0.559	0.024	0.000
	Het par 2	0.903	0.026	0.000
	sigma	0.147	0.002	0.000
	P(K=1)	0.274		
	P(K=2)	0.064		
	P(K=3)	0.662		

Table C1: Model estimates

Log-likelihood	-29770.49