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Returns to Education and Overeducation Risk: A Dynamic Model

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Returns to Education and Overeducation Risk: A Dynamic Model*

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Abstract

When individuals risk being overeducated for their jobs, returns to education might be lower and heterogeneous. To investigate this, we develop a novel framework that decomposes returns using an expected value conditional on overeducation risks and penalties. We estimate these components using Belgian data and a dynamic model of endogenous educational choices, overeducation, and wages. Our findings reveal that overeducated individuals experience a persistent wage penalty. However, as both medium and higher levels of education are associated with an overeducation risk, this risk usually plays a limited role in explaining average returns. Moreover, consistent with job polarization, this role is even positive for Bachelor's degrees as these degrees rather reduce the overeducation risks and the associated penalties. Finally, we find that overeducation generates heterogeneous realized returns among Master's graduates.

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

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1 Introduction

In recent decades, the percentage of the population with a higher education degree has increased markedly in most developed countries. Based on the overwhelming evidence on the positive average pecuniary and non-pecuniary returns to education (Gunderson and Oreopoulos, 2010; Oreopoulos and Salvanes, 2011), pursuing higher education indeed seems a worthwhile investment. However, these benefits may be limited for a sizable pool of graduates who start their careers in jobs that do not require a college degree (Verhaest and van der Velden, 2013; McGuinness et al., 2018). Indeed, these initially underemployed or so-called 'overeducated' graduates tend to face a wage penalty relative to well-matched graduates who obtain similar degrees (Hartog, 2000; Barnichon and Zylberberg, 2019). Moreover, regarding the non-pecuniary attributes of their jobs, these graduates also seem to be worse off (Verhaest and Omey, 2009). To make matters worse, several studies find that initial overeducation is persistent (Baert et al., 2013; Barnichon and Zylberberg, 2019) and also affects future wages negatively (Clark et al., 2017).

The literature has proposed several explanations for why graduates may be overeducated and, as a result, fail to capitalize on the potential benefits of college. One explanation is that overeducation results from search and matching frictions (Gautier, 2002; Dolado et al., 2009). Although this overeducation is often thought to be temporary, it may persist because of decreased on-the-job search (Holzer, 1987), locking in due to job-specific human capital investments (Pissarides, 1994), negative signaling (McCormick, 1990), or depreciation of underutilized skills (De Grip et al., 2008). Consequently, overeducation may lead to heterogeneous realized (ex-post) returns to college and generate risk in the schooling decision (Leuven and Oosterbeek, 2011). Another explanation is that overeducation results from heterogeneous skills across graduates (Allen and van der Velden, 2001; Chevalier, 2003; Agopsowicz et al., 2020). According to this explanation, overeducation may also be a channel that generates heterogeneity in expected (ex-ante) returns to college[1]. Finally, a more controversial but also quite popular explanation is that overeducation results from more general overinvestments in higher education (Charlot and Decreuse, 2005; McGuinness, 2006; Leuven and Oosterbeek, 2011). Due to labor market rigidities, one may expect labor markets to absorb an oversupply of high-skilled workers, at least partly due to a higher overall risk of overeducation. This, in turn, will

[1]Throughout this paper, we define ex-ante returns to college as returns expected prior to entering the labor market - that is prior to when any job match has been taken place. Ex-post returns, meanwhile, are defined as realized returns - that is the return observed subsequent to the job match.

reduce the average expected return to college across all graduates.

This paper develops a novel framework to investigate whether and how overeducation affects both the average rate of return to college and generates heterogeneous expected and realized returns to college. We frame the (unconditional) wage return to education as an expected value conditional on overeducation risk while accounting for differences in this risk and the overeducation penalty between levels of educational attainment. Derived from this, we decompose the wage return into three components representing (1) the return to education that may be realized in the absence of any labor market mismatches, (2) the effect of differences between education levels in the risk of overeducation, and (3) the effect of differences between education levels in the penalty to overeducation. The sum of the two latter components then represents the overall effect of a change in expected match quality that may be induced by investing in more education. We estimate these components using a dynamic model of joint educational choices and labor market outcomes. In this approach, career decisions are modeled as a sequence of choices that each depends on past decisions as well as on observed and unobserved characteristics (Heckman and Navarro, 2007; Heckman et al., 2018a, 2018b; Ashworth et al., 2021; Humphries et al., 2023). We estimate this model based on detailed longitudinal data about young' peoples careers in Belgium.

Our framework and estimation allow us to contribute in four main ways to the literature. First, we gauge the importance of overeducation in explaining wage returns to education in a more comprehensive way. 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. The conclusion that overeducation generates a wage penalty then stems from the finding that the return to years of overeducation is usually lower than that for years of required education (Hartog, 2000; McGuinness, 2006; Leuven and Oosterbeek, 2011). However, returns to years of overeducation and required education merely present returns conditional on the (ex-ante unknown) match status and do not consider how one's match quality is expected to be affected by attaining more education. Henceforth, as also argued by Leuven and Oosterbeek (2011), the wage penalty to overeducation may offer a misleading picture regarding the importance of overeducation in explaining the overall wage return to education. Our decomposition framework addresses this problem.

Second, we contribute to the question of whether this wage penalty to overeducation

presents a causal effect. Several strategies have been adopted in order to address endogeneity problems. The first 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 that differences in skills explain only a small percentage of the estimated penalty for overeducation. However, test scores are unlikely to capture all unobserved differences that may matter in this context. A second strategy is to rely on fixed-effects panel data methods (Frenette, 2004; Dolton and Silles, 2008; Verhaest and Omey, 2012; Mavromaras et al., 2013). Generally speaking, 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 (Korpi and Tåhlin, 2009). However, as this strategy requires the use of valid instruments both for education and overeducation, adopting this method in this context is extremely challenging (Leuven and Oosterbeek, 2011). By exploiting initial background conditions, local labor market conditions, informative outcomes such as study delay, track choice, and grades, as well as the panel structure of the data, we identify and account for unobserved determinants in an alternative way (Heckman et al., 2016; Ashworth et al., 2021; Humphries et al., 2023).

Third, few studies have already investigated whether obtaining a college degree increases the likelihood of being overeducated. Intuitively, one may expect this to be the case in the context of higher education expansion. In the longer run, however, labor markets are likely to generate more high-skilled vacancies in response (Ordine and Rose, 2017; Di Cintio, 2022). Moreover, as Goldin and Katz (2008) have argued, technology has been complementary to education for most parts of the past century.[2] And according to the routinization hypothesis, these technological advances have primarily served as substitutes for medium-skilled labor over recent decades, thus creating a polarized labor market (Autor et al., 2003; Goos et al., 2009). Because of this, attaining a college degree may thus just as well be an effective way to avoid overeducation. Indeed, a few descriptive studies conducted in the UK and Belgium have indicated that the probability of being overeducated is lower among the high-skilled than among the medium-skilled (Sloane et al., 1999; Verhaest and Omey, 2006).[3] However, whether

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

[3]By looking at a large range of European countries, Lessaer et al. (2015) meanwhile found overeducation 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 overeducation (i.e. a so-called 'realized matches' measure) that was adopted. We revisit this point in the methods section.

these findings are evidence of a causal link is unclear. Our analysis offers an interesting context in this respect as most of the individuals in our data entered the labor market between 1994 and 2003, a period for which the process of job polarization is well documented (Goos et al., 2009). Moreover, also the Belgian case is interesting because it combines a higher education system that is characterized by high levels of public subsidization and low tuition fees with (part-time) compulsory schooling until age 18. As a consequence, participation in higher education is quite high and only a small minority of young people enter the labor market without an upper secondary education degree.

Finally, we also contribute to the literature on the heterogeneity in returns to college. Several studies have shown the heterogeneity in both expected and realized returns to be substantial with a non-negligible part of the graduates even realizing negative returns (Arcidiacono, 2004; Rodríguez et al., 2016). Our modeling enables us to investigate in greater detail whether overeducation is a channel underlying these findings. Consistent with being a channel underlying differences in expected returns, many studies find overeducation to be negatively correlated with ability test scores or 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). However, even if graduates are more likely to be overeducated due to lower skill levels, this should not imply that their return to college is negligible. Not only does the literature indicate that the wage return for college conditional on being overeducated is still positive (Hartog, 2000), but there is also some evidence that employers prefer overeducated job seekers (Verhaest et al., 2018). Obtaining a college degree may therefore still improve one's ability to secure a medium-skilled job. By conditioning on both observable and unobservable characteristics in our model, we can investigate how differences in overeducation probabilities affect the full distribution of expected returns to college. Moreover, we can also investigate how this matching affects the distribution of realized (ex-post) returns by simulating the matching process conditional on the model's estimated parameters.

In line with the literature, our findings show that overeducation generates a persistent wage penalty. At age 23, the penalty is estimated to range from about 3% among those with an upper secondary education or bachelor's degree to around 8% among master's graduates. However, overeducation penalties only provide a partial view of the story. Relative to the literature, our decomposition framework shows that a part of the expected return to education comes from

a change in match quality across educational levels. This component is the sum of two different channels: one referring to the change in overeducation penalties and the other related to the change in overeducation risk. The change in match quality boils down to the overeducation penalties channel if and only if the overeducation risk is constant across educational levels. However, this is not the case. Indeed, although the change in match quality is moderately negative for obtaining an upper secondary and a master's degree, it is positive for a bachelor's degree. This striking result is motivated by the fact that obtaining a bachelor's degree substantially reduces both overeducation risk and overeducation penalties. This is likely driven by job polarization. Moreover, although we find that differences in overeducation risk reflect differences in expected (unconditional) wage returns across individuals, our results do not suggest that overeducation risk in and of itself reinforces this heterogeneity. However, with respect to master's degrees, we do find that overeducation generates substantial heterogeneity in realized (ex-post) returns to education. These results are more consistent with overeducation being indicative of search and matching frictions rather than considerable overinvestments in higher education.

The remainder of our paper is structured as follows. Section 2 introduces our conceptual framework and decomposition. In Section 3, we describe the institutional context. Section 4 introduces the dataset and the measurement of our key variables. In Section 5, we outline our dynamic discrete choice model. Section 6 presents the results. Finally, in Section 7, we discuss these results and conclude our paper.

2 Conceptual Framework

In this section, we develop a new conceptual framework to demonstrate how overeducation may affect both the average return to education and generate heterogeneous returns to education.

First, let us presume that the educational and labor market outcomes of an individual i can be summarized as follows:

$$e_i = f(X_i, \varepsilon_i^e) \tag{1}$$

$$o_i = g(e_i, X_i, \varepsilon_i^o) \tag{2}$$

$$w_{ia} = h(e_i, o_i, X_i, \varepsilon_i^{w_a}), \tag{3}$$

with (1) representing the educational attainment e_i and being a reduced-form equation of a

more extended model of human capital accumulation, (2) determining the overeducation status o_i once they leave the educational system and enter the labor market (modeled as a binary outcome with $o_i = 1$ when overeducated and $o_i = 0$ when adequately qualified for the job) and (3) reflecting one's subsequent wage w_{ia} at age a. We presume each of these three outcomes t to be a function of a set of exogenous characteristics and factors X_i (e.g., family background, gender, abilities, preferences, labor market conditions,...).[4] Finally, each outcome also depends on outcome-specific residual determinants ε_t, which are independent of one's characteristics X_i and prior endogenous outcomes. These residuals may, for instance, include outcome-specific preference shocks or, in the case of overeducation, random shocks due to search and matching frictions.

By substituting equation (2) in (3), we now rewrite the wage as a function of educational attainment e_i, exogenous characteristics X_i, and residual determinants ε_i:

$$w_{ia} = h\left(e_i, g(e_i, X_i, \varepsilon_i^o), X_i, \varepsilon_i^{w_a}\right) \tag{4}$$

With equation (4), we estimate the effect of educational attainment on wages unconditional of one's overeducation status. Henceforth, this allows us to identify the unconditional (total) wage return to education:

$$\frac{dw_{ia}}{de_i} = \frac{\partial w_{ia}}{\partial e_i} + \frac{\partial w_{ia}}{\partial o_i}\frac{do_i}{de_i}, \tag{5}$$

where the first term on the right-hand side of the equation represents the direct effect of educational attainment on wages, and the second term represents the indirect effect of educational attainment through its effect on overeducation. This indirect effect provides already a first channel through which overeducation may affect the return to education. However, as will be argued later in this section, also the direct effect may be affected by overeducation.

Rather than defining the return of an infinitesimally small change in the level of educational attainment, as is done in equation (5), it is more natural to evaluate the return to more specific, discrete levels of educational attainment. The unconditional wage return Δ_{iae} of educational attainment e for individual i at age a can be defined as the difference in expected wage conditional on e_i and the one conditional on a counterfactual level of educational attainment e_i':[5]

[4]To simplify the notation, we assume that X_i is time-invariant. In a more extended version of the model (as is estimated in our paper), one can differentiate between common time-invariant exogenous factors and exogenous factors that are time-variant (e.g., labor market conditions at the moment of the outcome).

[5]For the sake of simplicity, e_i' refers to the previous educational attainment in the majority of the paper (e.g., for Master's degree, a Bachelor's degree). However, we may also compute the returns relative to other educational

$$\Delta_{iae} = \mathbb{E}\left[w_{ia}|e_i\right] - \mathbb{E}\left[w_{ia}|e_i'\right] \tag{6}$$

The overeducation literature typically looks at the wage return conditional on one's match status rather than focusing on Δ_{iae}. We denote the match status m at educational attainment e_i to be either an adequate match, M, when $P_{ie}^o = 0$, or overeducation, O, when $P_{ie}^o = 1$, where P_{ie}^o is the probability of overeducation. Depending on one's match status at educational level e_i and the preceding level e_i', we identify four types of conditional wage returns that can be defined in the following way based on the overeducation probability P_{ie}^o at educational attainment e and the overeducation probabilty $P_{ie'}^o$ at the preceding level e':

$$\begin{aligned} \Delta_{iae}^{mm'} &= \mathbb{E}[w_{ia}|e_i, o_i] - \mathbb{E}[w_{ia}|e_i', o_i] = \\ &\left(P_{ie}^o\,\mathbb{E}[w_{ia}|e_i, o_i = 1] + (1 - P_{ie}^o)\,\mathbb{E}[w_{ia}|e_i, o_i = 0]\right) - \\ &\left(P_{ie'}^o\,\mathbb{E}[w_{ia}|e_i', o_i = 1] + (1 - P_{ie'}^o)\,\mathbb{E}[w_{ia}|e_i', o_i = 0]\right) \quad \text{for } m, m' \in \{M, O\} \end{aligned} \tag{7}$$

While Δ_{iae}^{MM} is the return to education presuming one would be adequately matched irrespective of one's level of educational attainment, Δ_{iae}^{OM} is the return to education when attaining more education induces one's match status to switch from an adequate match to overeducation. These two types of conditional returns are equivalent to two returns typically reported in the literature on overeducation: the return to (years of) required education and to (years of) overeducation. Moreover, by subtracting the return to required education from the return to overeducation, we obtain the so-called overeducation wage penalty ψ_{iae}:

$$\psi_{iae} = \Delta_{iae}^{OM} - \Delta_{iae}^{MM} = \mathbb{E}[w_{ia}|e_i, o_i = 1] - \mathbb{E}[w_{ia}|e_i, o_i = 0] \tag{8}$$

As shown, ψ_{iae} equals the difference in the expected wage while being overeducated and the expected wage while being adequately matched for educational attainment e.

This wage penalty to overeducation is often used to highlight the importance of overeducation in reducing the wage return to education. However, some individuals would also be overeducated without having completed more education, while others may even improve their match status by completing more education. Henceforth, we need to factor in conditional wage

attainment (e.g., a Master's degree relative to an upper secondary education degree). We include some results using other base levels than the previous level in Table C6 in the Appendix.

returns Δ_{iae}^{OO} and Δ_{iae}^{MO} as well when assessing the importance of overeducation in explaining unconditional returns to education.

We implement a decomposition approach to assess more explicitly how important overeducation is in explaining the unconditional return. To this end, by using equation (8), we first rewrite the expected wage ($\mathbb{E}\left[w_{ia}|e_i\right]$) as the sum of the expected wage when adequately matched ($\mathbb{E}\left[w_{ia}|e_i, o_i = 0\right]$) and the overeducation penalty (ψ_{iae}) weighted by the probability of overeducation (P_{ie}^{o}):

$$\begin{aligned}\mathbb{E}\left[w_{ia}|e_i\right] = (1 - P_{ie}^{o})\,\mathbb{E}\left[w_{ia}|e_i, o_i = 0\right] + P_{ie}^{o}\,\mathbb{E}\left[w_{ia}|e_i, o_i = 1\right] = \\ \mathbb{E}\left[w_{ia}|e_i, o_i = 0\right] + P_{ie}^{o}\psi_{iae}\end{aligned} \tag{9}$$

In addition, by adopting the same logic for the expected wage at the preceding level of education e' and by using equation (7), we obtain:

$$\Delta_{iae} = \Delta_{iae}^{MM} + P_{ie}^{o}\psi_{iae} - P_{ie'}^{o}\psi_{iae'} \tag{10}$$

Finally, by adding and subtracting $P_{ie'}^{o}\psi_{iae'}$ to the right-hand side of equation (10), we can decompose the unconditional wage return to education e into three subcomponents:

$$\Delta_{iae} = \underbrace{\Delta_{iae}^{MM}}_{\text{(A)}} + \underbrace{P_{ie'}^{o}\left(\psi_{iae} - \psi_{aie'}\right)}_{\text{(B)}} + \underbrace{(P_{ie}^{o} - P_{ie'}^{o})\psi_{iae}}_{\text{(C)}} = \Delta_{iae}^{MM} + \Delta_{iae}^{Q} \tag{11}$$

where (A) represents the return in case of perfect matching, (B) is a subcomponent attributed to a potential difference in overeducation penalties between e and e', and (C) is a subcomponent attributed to a potential difference in overeducation risk between e and e'. The latter subcomponent is also equivalent to the indirect effect of education on wages as defined by equation (5).

Importantly, Δ_{iae} collapses to (A) when the expected match quality is identical across levels of educational attainment. The sum of (B) and (C) (i.e. Δ_{iae}^{Q}), meanwhile, is a more general component that measures the contribution of any change in expected match quality that may be induced by investing in more education. And given that this component is merely driven by changes in overeducation penalties and probabilities across e and e', it is apparent that a focus on absolute overeducation penalties and probabilities may lead to misleading inferences about the importance of overeducation.

Our decomposition may be implemented for both the average Δ_{iae} and for its distribution. For instance, due to differences in innate abilities, individuals may differ in their overeducation risk (cf. equation (2)) and, therefore, in their expected unconditional return. This distribution of expected un-conditional returns is based on the assumption that one's overeducation status is not precisely known (i.e., it is the expected return prior to the matching to a first job). However, due to random shocks in both overeducation (i.e., $\varepsilon_i^o \neq 0$) and wages (i.e., $\varepsilon_i^{w_a} \neq 0$), this distribution will deviate from the distribution of returns that are realized in practice. For instance, even if the overeducation probability is small for i, search and matching frictions may still cause i to end up in a bad match. Hence, to gauge the extent to which overeducation contributes to heterogeneous realized returns as well, one may also simulate the distribution of (unconditional) returns that may be realized based on a random matching process in both overeducation in the first job and wages in later jobs, and compare it to the distribution of returns that may be realized while presuming perfect matching in the first job.

3 Institutional Setting

We use data on individuals' educational and early labor market careers in Flanders, the Northern Dutch-speaking region of Belgium. In Flanders, compulsory education starts when the child turns 6 until their 18th birthday or until June 30th of the year when they turn 18. Primary education usually starts at 6 and consists of 6 consecutive grades. Subsequently, at the age of 12 in the case of no delay, pupils enter secondary education (SE). Secondary education consists of four tracks: general, technical, art, and vocational, with the technical or art tracks being available from the 3rd grade in SE onwards. From age 15 onwards, students may also opt for a part-time vocational track combined with three to four days of apprenticeship training in a firm. After passing the 2nd, 4th, and 6th grade in secondary education, individuals receive a certificate with the latter two certificates usually conceived as equivalent to a lower (LS) and upper (US) secondary education qualification, respectively. With a US qualification in the general, arts, or technical track, or after passing a 7th grade in the vocational track, individuals may enter higher education without completing any entrance exam (except for medicine).

In higher education (HE), students may participate in a bachelor's program (BA) either at a vocationally-oriented college or at an academically-oriented university, with the latter providing direct access to a master's program (MA). Students may also start in an MA program

after obtaining a vocational BA degree, conditional on participating in a bridging program that usually takes one year. When our sample entered higher education, which is the period before the Bologna reform, the system was slightly different as individuals were able to choose between (i) a short-term (3 years) or (ii) a long-term program (4 or more years) at a college, or (iii) a long-term program at university. By law, the old short-term and long-term degrees have been declared to be equivalent to BA and MA degrees respectively. Henceforth, we will use this new terminology throughout the paper when we refer to those who have obtained a short- or long-term degree. In addition, to preserve the consistency with the current system, we also presume those who have passed the 3rd grade in a long-term program to have obtained a degree that is equivalent to a BA Degree.[6]

4 Data

4.1 Sample

We use the SONAR data, which includes representative samples of three cohorts (birth years 1976, 1978, and 1980) of approximately 3,000 individuals per cohort who were surveyed for the first time at age 23. These surveys were supplemented with 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 labor market outcomes, gleaned by recording each educational choice from age 6 onwards and a monthly registering of core information on labor market history.[7] In addition, the dataset includes a large set of variables related to the family background and information on the overeducation status and wages, measured at the start of the first job as well as at the moment of the various surveys (ages 23, 26, and 29).

To ensure the estimated model remains tractable, we remove from the initial sample those individuals (i) who experienced more than one year of delay at the start of their primary education (76 individuals) and (ii) those who have special needs that are catered for in schools providing special care (124 individuals). Moreover, we remove another 638 individuals with

[6]Both in the old and the new system, three completed years of higher education are equivalent to 180 earned credits. Although in the pre-Bologna system, many long-term programs awarded already a so-called 'candidate qualification' after just two grades, these qualifications are usually not considered equivalent to a bachelor's degree. Therefore, we follow the logic of the current system to obtain a bachelor's degree at university.

[7]To avoid recall errors, this information has been recorded based on a calendar approach in which the respondents gradually reconstructed their careers.

(iii) inconsistent, erroneous, or incomplete data regarding the exogenous variables (cf. infra) and their educational careers. Our final sample, which is used to estimate the equations related to educational outcomes, includes 8,162 individuals. We refer to Section A and Table A1 in the Appendix for a discussion of the dataset construction.

4.2 Exogenous Variables

At each stage of our model, we control for the following exogenous individual background characteristics: gender, foreign origin, years of education of the mother and the father (beyond primary education), number of siblings, year of birth, and day of birth within the calendar year. Most of these characteristics are frequently included in dynamic discrete choice models on educational choices (e.g., Cameron and Heckman, 1998, 2001; Belzil and Poinas, 2010; Heckman et al., 2018a, 2018b; Baert et al., 2022). In addition, we include the unemployment rate at the district level to account for differences in labor market conditions. This time-varying variable is measured at the moment of each outcome. Table 1 includes descriptives on these variables.

4.3 Educational Choices and Outcomes

Our dynamic model, which is an extended version of the model introduced in Section 2, includes 17 sequential outcomes (see Table 1). With respect to the educational career (cf. equation (1)), these outcomes include the delay at the start of primary and secondary education along with the enrollment, track choice, and attainment related to the following four crucial stages of secondary and higher education: lower secondary education (LS), upper secondary education (US), the bachelor's level in higher education (BA), and the master's level (MA).

Enrollment in these four stages is defined as having enrolled in the 3rd grade of secondary education (LS)[8], the 5th grade of secondary education (US), the 1st grade of higher education (BA), and the 4th grade of higher education (MA). The track choice refers to the (first) year of enrollment in each of these stages. It distinguishes between the general track (in secondary education) or academic track (in higher education) and other tracks. The academic track in higher education includes all university programs, while the non-academic track includes programs at

[8]Strictly speaking, individuals already enroll in lower secondary education from the 1st grade of secondary education onward. However, as this is the case for (almost) all individuals in our dataset, we adjust the definition towards enrollment in the 3rd grade.

Table 1: Descriptive Statistics

	Full Sample	Adequately Matched	Overeducated
N	8,162	3,451	3,760
A. Exogenous variables:			
Female	0.494 (0.500)	0.490 (0.500)	0.500 (0.500)
Number of siblings	1.669 (1.422)	1.698 (1.435)	1.631 (1.414)
Foreign origin	0.056 (0.231)	0.059 (0.235)	0.048 (0.214)
Education Mother	5.738 (3.437)	5.547 (3.374)	5.647 (3.411)
Education Father	6.217 (3.675)	6.049 (3.557)	6.004 (3.638)
Birthday date/100	1.718 (1.002)	1.708 (1.003)	1.727 (1.008)
Cohort 1978	0.338 (0.473)	0.339 (0.474)	0.326 (0.469)
Cohort 1980	0.345 (0.475)	0.335 (0.472)	0.348 (0.476)
B. Endogenous variables:			
B.1. Schooling outcomes			
1.Delay Start Primary Education	0.015 (0.123)	0.014 (0.120)	0.015 (0.120)
2.Delay Start Secondary Education	0.101 (0.302)	0.114 (0.318)	0.094 (0.292)
3.Enrollment LS	0.991 (0.095)	0.980 (0.140)	1.000 (0.000)
Enrollment LS General	0.524 (0.499)	0.474 (0.499)	0.520 (0.500)
4.LS Degree	0.954 (0.209)	0.898 (0.303)	1.000 (0.000)
5.Enrollment US	0.442 (0.497)	0.383 (0.486)	0.439 (0.496)
Ernollment US General	0.938 (0.242)	0.873 (0.333)	0.989 (0.105)
6.US Degree	0.887 (0.317)	0.801 (0.399)	0.956 (0.205)
7.Enrollment BA	0.636 (0.481)	0.574 (0.495)	0.647 (0.478)
Enrollment BA Academic	0.214 (0.410)	0.153 (0.360)	0.216 (0.412)
8.BA Degree	0.477 (0.499)	0.427 (0.495)	0.492 (0.500)
BA Degree cum Laude	0.167 (0.373)	0.166 (0.372)	0.161 (0.368)
BA Degree magna cum Laude	0.032 (0.176)	0.032 (0.175)	0.028 (0.166)
9.Enrollment MA	0.215 (0.411)	0.120 (0.325)	0.249 (0.432)
Enrollment MA Academic	0.146 (0.353)	0.090 (0.286)	0.157 (0.364)
10.MA Degree	0.193 (0.395)	0.115 (0.319)	0.244 (0.430)
MA Degree cum Laude	0.091 (0.287)	0.060 (0.237)	0.110 (0.313)
MA Degree magna cum Laude	0.031 (0.173)	0.023 (0.149)	0.033 (0.179)
B.2. Labor market outcomes:			
11.Overeducation first job	0.461 (0.498)	0.000 (0.000)	1.000 (0.000)
12.Wage selection at age 23	0.537 (0.499)	0.601 (0.490)	0.569 (0.495)
13.Hourly wage at age 23	7.352 (1.587)	7.427 (1.618)	7.260 (1.558)
14.Wage selection at age 26	0.414 (0.493)	0.454 (0.498)	0.447 (0.497)
15.Hourly wage at age 26	8.128 (1.859)	8.128 (1.855)	8.100 (1.878)
16.Wage selection at age 29	0.385 (0.487)	0.417 (0.493)	0.430 (0.495)
17.Hourly wage at age 29	8.565 (1.854)	8.571 (1.830)	8.525 (1.831)

Notes: Educational attainment levels are coded as LS (lower secondary), US (upper secondary), BA (lower tertiary or Bachelor's degree), MA (higher tertiary or Master's degree). Endogenous variables are indexed from 1 to 17, following the outcomes t of the model (See Figure 2).

vocationally oriented colleges. Furthermore, besides the obtainment of a degree at each of the four stages, we also account for whether they have obtained their BA and MA degree with a *cum fructu*, a *cum laude*, or (at least) a *magna cum laude* grade.

Table 1 includes the descriptive statistics for each outcome. Only a small minority of the sample (11.3%) can be categorized as low-skilled (i.e., less than US Degree), while the medium- (US degree) and high-skilled (at least a BA degree) represent 42.1 and 48.6% of the sample, respectively (see also Table 2).

4.4 Overeducation

The next outcome of interest in our model is overeducation (cf. equation (2)), defined as having attained a level of education above the level required to do one's job. We focus on overeducation at the first job with a standard labor contract, which excludes internships, apprenticeships, or student work.

To measure overeducation, the literature has adopted a wide range of methods that can be subdivided into four broad categories: (i) job analysis (JA), (ii) direct self-assessment (DSA), (iii) indirect self-assessment (ISA), and (iv) realized matches (RM) methods (McGuinness, 2006; Verhaest and Omey, 2006; Leuven and Oosterbeek, 2011). JA methods are usually based on occupational classifications that define the required level of education based on the assessment of experts. Self-assessment methods rely on the worker's assessment, either by asking directly whether he or she is overeducated (DSA) or indirectly by querying about the required level of education to do or get the job (ISA). Finally, RM methods measure the required level by the average or modal level of education within an occupation. Each of these methods has some disadvantages. JA and RM methods may insufficiently account for requirements heterogeneity within jobs with the same occupational title. Moreover, while JA methods require frequent updates to account for technological change, requirements measured by RM may be largely endogenous to the composition of the labor force regarding their educational attainment. Finally, DSA and ISA measures are likely to be vulnerable to various cognitive biases.[9]

Given the richness of our data, we can circumvent these problems at least partly by combining the information on three of these types of measures. Our first measure is a JA measure based on the Standard Occupation Classification of Statistics Netherlands. Second, we include

[9]For instance, due to a lack of expertise in this respect, individuals may find it difficult to gauge the true requirements of their jobs, or they may answer in a socially desirable way, thus inflating their status.

an ISA measure based on the survey question: 'What is (was), in your opinion, the most appropriate educational level to execute your first job?'. As this question was not included in the survey for the 1976 cohort, we implemented a modified procedure following Baert et al. (2013). This modified approach measures the required educational level of an individual's job by the mean worker-assessed required level within her occupation. Our third measure is a DSA measure derived from the survey question: 'According to your opinion, do you have a level of education that is too high, too low, or appropriate for your job?'.

Our choice to rely on this set of measures is based on three main arguments. First, these measures are the most closely connected with the overeducation concept as defined in the literature. Second, given our focus on the relationship between educational attainment and overeducation, it is inappropriate to include measures that are endogenous to the educational composition of the workforce, such as those based on RM. Third, these measures result from three relatively independent assessments, conducted by a job expert (JA), the worker (DSA), and the co-workers within the occupation (ISA). Hence, systematic errors across two or three of these measures are expected to be limited. Based on these three measures, we construct a new combined measure. This measure is constructed using a latent factor approach, which controls for measurement error and assumes each of the three usual measures to capture one single dimension of overeducation. The main intuition is that the three individual measures (JA, ISA and DSA) are noisy measures of a single latent variable:

$$Y_{im} = \mu_{im} + \lambda_m \theta_i^{BM} + \varepsilon_{im} \quad \text{with } m \in M = \{JA, ISA, DSA\} \tag{12}$$

where there are i individuals and m measures. $Y_{im}, ..., Y_{iM}$ are the individual measures, $\mu_{im}, ..., \mu_{iM}$ are the measurement intercepts, and $\lambda_m, ..., \lambda_M$ are the measurement "factor loadings". Our benchmark measure (LF) defines an individual to be overeducated when the latent variable θ^{BM} exceeds zero.

As reported in Table 2, about 43% of our sample is overeducated in the first job based on our benchmark measure (LF). Moreover, besides being more pronounced among those with an MA degree, we also find overeducation to be substantial among the medium-skilled (US). The three individual measures deliver a similar pattern of overeducation across the levels of educational attainment. In Table A2 in Appendix A, we also report the top and bottom occupations by their fraction of overeducated workers. Unsurprisingly, occupations with a high overeducation incidence are low-skilled service jobs such as shelf fillers, cashiers, or waiters. Meanwhile,

Table 2: Educational Attainment and Overeducation Measures

	Educational Attainment					
(ISCED Code)	Dropout *(0,1)*	LS Degree *(2)*	US Degree *(3,4)*	BA Degree *(5 Bachelor)*	MA Degree *(5 Master)*	Total
N (%)	4.9%	6.9%	42.1%	27.8%	18.3%	7,211
Benchmark Measure						
Latent Factor (LF)	0.000	0.210	0.493	0.319	0.673	0.434
Individual Measures						
Job Analysis (JA)	0.000	0.306	0.575	0.461	0.631	0.507
Indirect Self-Assessment (ISA)	0.000	0.124	0.466	0.283	0.671	0.406
Direct Self-Assessment (DSA)	0.145	0.271	0.321	0.190	0.307	0.270
Alternative Measures						
Indirect Self-Assessment Median (ISAm)	0.000	0.228	0.252	0.248	0.658	0.311
Latent Factor Median (LFm)	0.000	0.332	0.575	0.464	0.698	0.521

Notes: Educational attainment levels are coded as Dropout, LS (lower secondary), US (upper secondary), BA (lower tertiary or Bachelor's degree), MA (higher tertiary or Master's degree).

occupations with a low overeducation incidence include medical practitioners, software developers, and legal professionals.

While we rely on the LF measure in our benchmark analysis, we also report the results of some robustness analyses based on the individual measures. Moreover, we also conduct a sensitivity analysis based on an alternative latent factor measure (LFm), which replaces our ISA measure by a measure that relies on the median worker-assessed required level within an occupation (ISAm) instead of on the mean. As shown in Table 2, this alternative LF measure delivers a similar pattern of overeducation as our benchmark LF measure, even if this is less so the case for ISAm.[10]

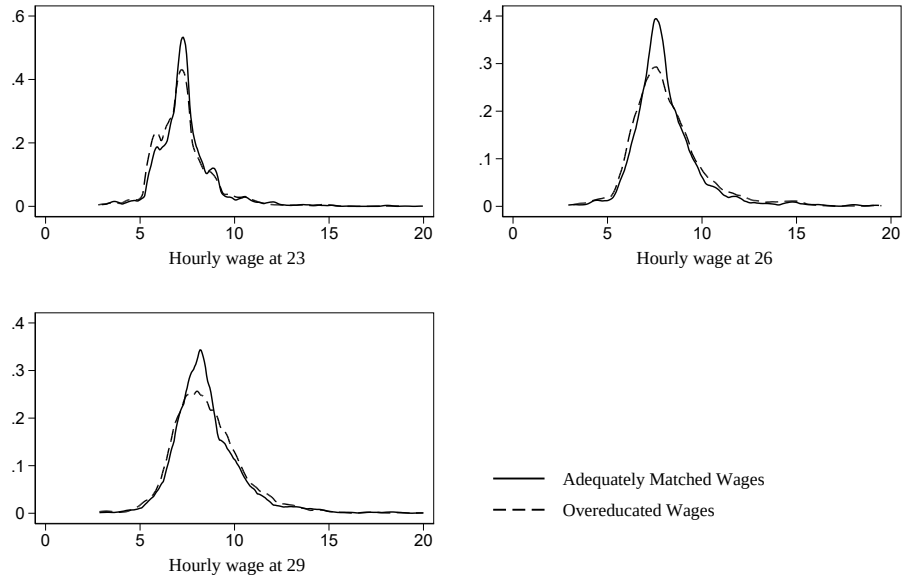
4.5 Wages

To maintain the sequentiality of our model, which is a precondition to identifying causal effects based on our method, we analyze the wages at ages 23, 26, and 29 rather than those at the start of the first job (cf. equation (3)). The estimated wage effects of overeducation in our model are to be interpreted as reduced-form effects that result from, among other things, its effect on later mismatch status. As shown by Baert et al. (2013) based on a subsample of the same SONAR

[10]This is due to the fact that, in most low-skilled occupations, individuals either assign LS dropout or an US degree as required level instead of an LS degree. A limited number of observations therefore may have a substantial impact on the median (shifting from dropout to US degree). The (rounded) mean, meanwhile, is more stable and offers a better representation of the consensus view within the occupation. Hence our decision to rely on the latter for our standard ISA measure.

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 also to affect future wages. Moreover, this would also be consistent with the findings of Clark et al. (2017) for the US and a few studies on other countries that found that overeducated workers experience no more wage growth than other workers (Büchel and Mertens, 2004; Korpi and Tåhlin, 2009).[11]

Figure 1: Distribution of Wages by Overeducation



We include log real hourly net wages. Due to missing data, the number of observations in the wage equations drops to 4,407, 3,379, and 3,142 for the ages 23, 26, and 29, respectively. With respect to age 23, data is missing for two main reasons. First, a significant proportion of the individuals were still in education or without jobs at this age. Second, not all individuals were queried about their wage at age 23.[12] With respect to age 26 and age 29, meanwhile, missing data on wages are primarily caused by a lack of surveying (for the 1978 cohort at age 26, and for the 1980 cohort at age 29) or due to attrition. Missing data due to respondents' refusal to answer or because of wage outliers are less important for each of the three points of measurement. As these missing data are unlikely to be random, we account for this in our analysis by adding three selection equations to our model (cf. infra).[13]

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

[12] For the 1978 and 1980 cohorts, those who were still in a first job that had started within the last year were precluded from answering these questions, while for the 1976 cohort, none of the individuals who were still in their first job (irrespective of when it started) were asked to indicate their wage.

[13] To keep our model tractable, we do not differentiate between missings due to non-employment and missings due to other reasons.

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 at each age positioned to the left of the wage distribution of adequately matched individuals.

5 Econometric Strategy

5.1 Dynamic Treatment Effects

This paper develops a dynamic model of educational choices and labor market outcomes to estimate the components derived in Section 2. We develop a dynamic model following a large literature on educational and labor market choices (Cameron and Heckman, 1998, 2001; Heckman and Navarro, 2007; Belzil and Poinas, 2010; Declercq and Verboven, 2018; Heckman et al., 2018a, 2018b; Ashworth et al., 2021; Joensen and Mattana, 2021; Neyt et al., 2022; De Groote, 2023; Humphries et al., 2023). These models are characterized by a sequential structure, with each choice opening up the possibility of future choices. This structure is consistent with the organization of the education system, whereby obtaining access to a particular stage (e.g., tertiary education) is conditional on obtaining a qualification at the previous stage (e.g., a higher secondary education degree).

We estimate dynamic treatment effects based on this model. The joint probability of a given set of states and actions can be estimated non-parametrically from the data under two key assumptions: (i) the unobservable shocks are i.i.d. over time and across individuals with distribution G_ε, and (ii) the state transition variables depend only on the previous period, but not on the shocks from the previous period (Hotz and Miller, 1993; Rust, 1994; Arcidiacono and Miller, 2011; Humphries et al., 2023).[14] Therefore, we avoid solving the full structural dynamic discrete choice model and simulate the dynamic treatment effects, as the impact of a choice at a given time on future choices and outcomes (Heckman et al., 2016; Humphries et al., 2023).

This approach is often referred to as a methodological middle-ground between the reduced-form approach and the structural 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

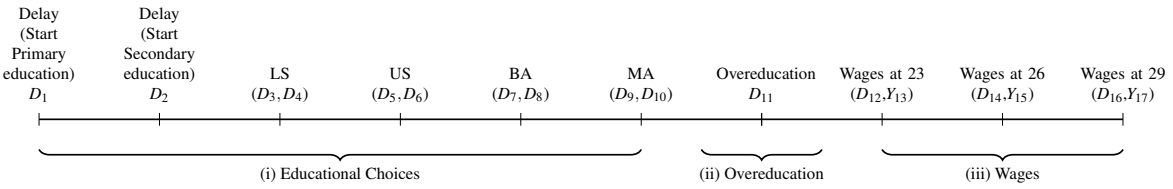
[14]This is achieved by imposing assumptions used for conditional choice probabilities (CCP) estimation of fully-specified dynamic discrete choice models (Humphries et al., 2023).

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., 2018a, 2018b). Another major advantage of this approach is that it lets us decompose the treatment effects into direct and total effects associated with later educational choices (Heckman et al., 2018a, 2018b).

5.2 Dynamic Model

We extend the version of the model introduced in Section 2. This captures the dynamic relationship between schooling choices, human capital formation, and labor market outcomes for each individual i. In line with our framework, we have three main sets of choices and outcomes: (i) educational choices, (ii) overeducation, and (iii) wages at age $a \in \{23, 26, 29\}$.

Figure 2: Model



As shown in Figure 2, we model choices from the start of primary education to age 29. Let t denote the sequence of choices and outcomes in the model. At $t = 1$, students may experience a delay of their entry into primary education, $D_1(\kappa_1)$, with $\kappa_1 \in \mathscr{K}_1 = \{0, 1\}$ and $\kappa_1 = 1$ indicating delayed entry. At $t = 2$, students may also experience a delay of their entry into secondary education, $D_2(\kappa_2)$, with $\kappa_2 = \kappa_1$.

Next, individuals may enroll in secondary education ($t = \{3, 5\}$) and tertiary education ($t = \{7, 9\}$), represented by $D_t(\kappa_t)$ with $\kappa_t = \kappa_3 \in \mathscr{K}_3$. Let $\kappa_3 \in \mathscr{K}_3 = \{0, 1, 2\}$ denote no enrollment, enrollment in a vocational degree, and enrollment in general (academic for tertiary education) degree, respectively. For US, BA, and MA degrees, individuals may enroll only if they completed their previous educational attainment. At $t = \{4, 6\}$, if they enrolled in the previous period ($D_{t-1}(\kappa_{t-1}) > 0$), individuals may attain an LS and a US degree ($D_t(\kappa_t) = 1$), respectively. Similarly, at $t = \{8, 10\}$, if enrolled in $t - 1$, ($D_{t-1}(\kappa_{t-1}) > 0$), individuals may attain a BA degree and an MA degree with a specific grade, represented by $D_t(\kappa_t) = \kappa_8 \in \mathscr{K}_8 = \{0, 1, 2, 3\}$. Let $\mathscr{K}_8 = \{0, 1, 2, 3\}$ denote not graduating or graduating with *cum fructu*, *cum laude*, or *magna cum laude*, respectively.

The last set of choices and outcomes relates to the labor market. At $t = 11$, they start

their first job, where they may be either adequately matched ($D_t(\kappa_t) = 0$) or overeducated ($D_t(\kappa_t) = 1$). Finally, at $t = \{12, 13, 14, 15, 16, 17\}$, we register the outcomes with respect to the wages at later ages. More particularly, $D_t(\mathscr{K}_t)$ with $\kappa_t = \kappa_1 \in \mathscr{K}_1 = \{0, 1\}$ for $t = \{12, 14, 16\}$ are binary choices indicating whether individuals are selected in the wage equation at age 23, 26 and 29, respectively, while D_t for $t = \{13, 15, 17\}$ represent the observed (continuous) wages at these ages themselves.

The discrete choices of the model ($t \in \{1, ..., 12, 14, 16\}$) are characterized by the maximization of a latent utility variable $U_{it\kappa_t}$:

$$D_t(\mathscr{K}_t) = \underset{\kappa_t \in \mathscr{K}_t}{\operatorname{argmax}} \left(U_{it\kappa_t} \right) \text{ for } t \in \{1, ..., 12, 14, 16\} \tag{13}$$

We presume these choices to be determined by a vector of preceding outcome-specific endogenous choices V_{it}, exogenous time-invariant characteristics X_i, and outcome-specific shocks ε_{it} i.i.d. over t and across i. In the context of our dynamic model, we also include time-variant observed characteristics R^{it}, such as local labor market conditions and unobserved exogenous determinants that are correlated with the preceding endogenous choices (abilities, motivations, preferences). Finally, regarding the overeducation equation ($t = 11$), we also include a set of interactions between the observed characteristics and the educational choices, track choices and grades (I_{it}) to directly account for potential differences across individuals in the effects of the endogenous educational choices.[15] We thus approximate $U_{it\kappa_t}$ using the linear index:

$$U_{it\kappa_t} = \beta_{0t} + \beta_{Xt} X_i + \beta_{Rt} R_{it} + \beta_{Vt} V_{it} + \beta_{It} I_{it} + v_{it} \text{ for } t \in \{1, ..., 12, 14, 16\} \tag{14}$$

Regarding the wage equations ($t \in \{13, 15, 17\}$), we consider a log-linear specification with a similar set of determinants as for overeducation. Moreover, to directly address potential differences in overeducation penalties across levels of education and individuals, I_{it} also includes interactions between overeducation and the observed exogenous characteristics, endogenous educational choices, and the unobserved heterogeneity:

$$Y_{it} = \beta_{0t} + \beta_{Xt} X_{it} + \beta_{Rt} R_{it} + \beta_{Vt} V_{it} + \beta_{It} I_{it} + v_{it} \text{ for } t \in \{13, 15, 17\} \tag{15}$$

[15] Our model also accounts more indirectly for heterogeneity in the effects of educational attainment on overeducation through the effects that the exogenous characteristics and prior endogenous choices may have on the track choice and grade that is associated with one's increased attainment.

In the wage equations, we do not include wages at earlier ages. We made this decision because wages are not consistently observed across all ages for all cohorts. Therefore, the estimated effects in these wage equations are to be interpreted as reduced-form effects that also consider indirect effects through prior wages.

5.3 Selection Bias and Identification

We need to address two types of selection bias. First, classical selection bias results from the fact that the treated individuals may differ from the control group in several respects that are not covered by the observable exogenous variables.[16] Second, the estimates may be biased due to dynamic selection bias. This is because of the increasing negative correlation between a treatment and the unobservable characteristics as students progress in their educational careers (Cameron and Heckman, 1998, 2001).

To account for these two types of biases, we apply the following factor structure to the error term v_{it}:

$$v_{it} = \omega_{kt}\eta_k + \varepsilon_{it} \tag{16}$$

in which η_k is a random effect, which is independent of the observed exogenous characteristics (Z_i and R_{it}) and independent of the outcome-specific residuals ε_{it}. This random effect includes any variation in the unobserved exogenous determinants not specific to one of the outcomes and not captured by the vectors of observed exogenous individual characteristics (Z_i and R_{it}). Moreover, as all the treatments of interest are modeled as outcomes of earlier choices (and, therefore, are dependent on the unobserved random effect), our approach also accounts for the former, more classical selection problem.[17]

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).[18] We assume this distribution is characterized by an a priori unknown number of K different heterogeneity types with type-specific heterogeneity parameters ω_k^t for each outcome. This prevents us from having to rely on strong distributional assumptions and,

[16] For instance, individuals who managed to attain a particular educational degree are likely to have different abilities and motivations relative to those who dropped out. If these abilities and motivations also drive labor market outcomes, this would lead to a biased estimate of the labor market return to this degree.

[17] This is different for selection problems related to Z_i and R_{it}, 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.

[18] 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.

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 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 assuming all treatments and outcomes are part of the same, more general human capital decision-making process. This implies that 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 started before enrollment in lower secondary education, which is the earliest choice of interest in the model. Hence, we decide to start the model with a delay at the start of primary school (at the age of six) as the first outcome. This assumption is substantially weaker than the 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 other decisions that are a crucial part of this decision process but are beyond the scope of the analysis (Cockx et al., 2019). Hence, we also decided to model the track choice, which is strongly selective in Flanders and generally considered an important determinant of subsequent educational and labor market outcomes. In a similar vein, also grades and delays provide essential information to identify the unobservable component.

As a second source of identification, we follow Arcidiacono (2005), Heckman and Navarro (2007), Heckman et al. (2016, 2018a, 2018b), Ashworth et al. (2021), and Humphries et al. (2023) 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 labor market outcomes (cf. Baert et al., 2022). We thus assume that the delay in primary education affects the labor market outcomes only indirectly through its effect on the delay at the start of secondary education. As the labor market effects of delay at the start of secondary education are unlikely to depend upon when it occurred, this is a reasonable assumption.

5.4 EM Algorithm and Model Selection

This model is estimated using an Expectation-Maximization (EM) algorithm (Dempster et al., 1977; Arcidiacono and Jones, 2003; Arcidiacono, 2005). It is composed of (i) an expectation and (ii) a maximization step, both of which 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 $k \in K$: $\mathscr{L}_i(Z_i, R_i, V_i, \omega_k; \theta)$. Indeed, for each type k, we know the type- and outcome-specific likelihood, $\ell_{it}(\gamma_k)$, and the total expected likelihood weighted by the probability of being in each type k, $\pi_{k,i}$:

$$\mathscr{L}_i = \sum_{i=1}^{I} \left[\sum_{k=1}^{K} \pi_k \log \left(\prod_{t=1}^{T} \ell_{it}(\gamma_k) \right) \right], \tag{17}$$

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

$$\hat{p}_{ki} = \frac{\pi_{ki}\mathscr{L}_i}{\sum_{k=1}^{K} \pi_{ki}\mathscr{L}_i} \tag{18}$$

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.

$$\hat{\theta} = \arg\max_{\theta} \sum_{i=1}^{I} \sum_{k=1}^{K} \hat{p}_{ki}(k|X_{it}, R_{it}, V_{it}, \pi) \left(\sum_{t=1}^{T} \ln(\ell_i^t(X_{it}, R_{it}, V_{it}, \omega_k; \theta)) \right) \tag{19}$$

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

To identify the optimal number of heterogeneity types k, we re-estimate the model by gradually adding up to four types. In Table B3 in the Appendix B, we report the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) values on each of these models. We select the model with three heterogeneity types ($K = \{1,2,3\}$) as our benchmark model based on these criteria. For $k = 2$ and $k = 3$, η_2 and η_3 enter the likelihood function as an additional intercept.

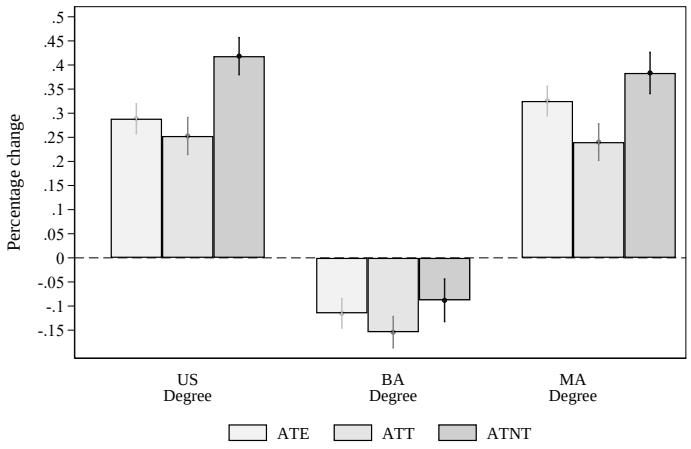
6 Results

In this section, we first estimate the impact of educational attainment on overeducation. In a second subsection, we report the results on the returns conditional on match status and those on the overeducation wage penalties. Third, we simulate average unconditional returns to education and use the results reported in the first two subsections to decompose these returns. Fourth, we consider how overeducation generates heterogeneous returns. All of these results are simulated based on our benchmark model (see the parameters in the Appendix D). In the final subsection, we conduct sensitivity analyses by using alternative overeducation measures and different versions of the model.

6.1 Overeducation and Educational Attainment

Figure 3 shows the Average Treatment Effect (ATE), Average Treatment Effect on the Treated (ATT), and Average Treatment Effect on the Untreated (ATNT) of each educational attainment 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.

Figure 3: Impact of Educational Attainment on Overeducation (ATE, ATT and ATNT)

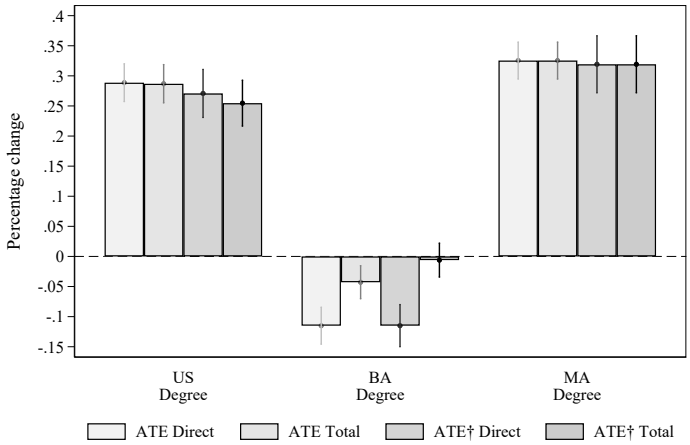


Notes: ATE is computed using individuals in educational attainments e and e', ATT includes individuals holding educational attainment e and ATNT those who attained e'. For US degrees, e' includes both individuals with an LS Degree and Dropouts.

The effect of educational attainment is non-linear. Entering the labor market with a US degree increases the probability of overeducation relative to entering the labor market with only an LS degree. The opposite is true concerning a BA degree relative to a US degree. Both effects

are substantial, with an US degree increasing the likelihood of overeducation by 30 percentage points and a BA reducing this likelihood by 10 percentage points. Investing in an MA again increases this probability. These results align with a polarized labor market and challenge the idea that overeducation is primarily a problem among tertiary education graduates. When differentiating between the ATT and ATNT, we find substantial evidence of sorting on gains. Relative to their untreated counterparts, treated individuals experience a substantially lower effect of obtaining a US or MA degree on their overeducation probability: a difference of 16 and 14%-points, respectively. Regarding obtaining a BA degree, the reduction in overeducation risk is greater for treated individuals relative to untreated ones (7%-points).

Figure 4: Impact of Educational Attainment on Overeducation (ATE and ATE†, Direct and Total effects)



Notes: ATE† includes all individuals in the sample, while ATE only selects individuals who attained either e or e'. Total also includes the indirect effect of enrolling in educational levels beyond e, while direct only includes the effect of educational attainment e.

Figure 3 reports the ATE for individuals at the final nodes, i.e. individuals holding educational attainment e and e' (Heckman et al., 2018a).[19] In Figure 4, we look at how the effects change when the sample is extended beyond the final nodes (ATE†) and when considering total (instead of direct) effects. The treatment effect of starting and obtaining a US (BA) is smaller (larger) when the total ATE† effect is considered. Because of the dynamics in our model, obtaining a US degree not only increases overeducation risk directly but grants access to higher levels of educational attainments with lower risk. The difference in outcomes between the total ATE and total ATE† stems from the fact that individuals with a weaker impact of a higher edu-

[19]E.g., for an MA degree, this would coincide with individuals holding a BA degree and an MA degree. For ATE† meanwhile, we select the full sample, including individuals with a US and an LS degree as well.

cation degree on overeducation tend to self-select into higher educational levels. Consequently, they are less likely to be included in the calculation of the ATE.

6.2 Conditional Returns to Education

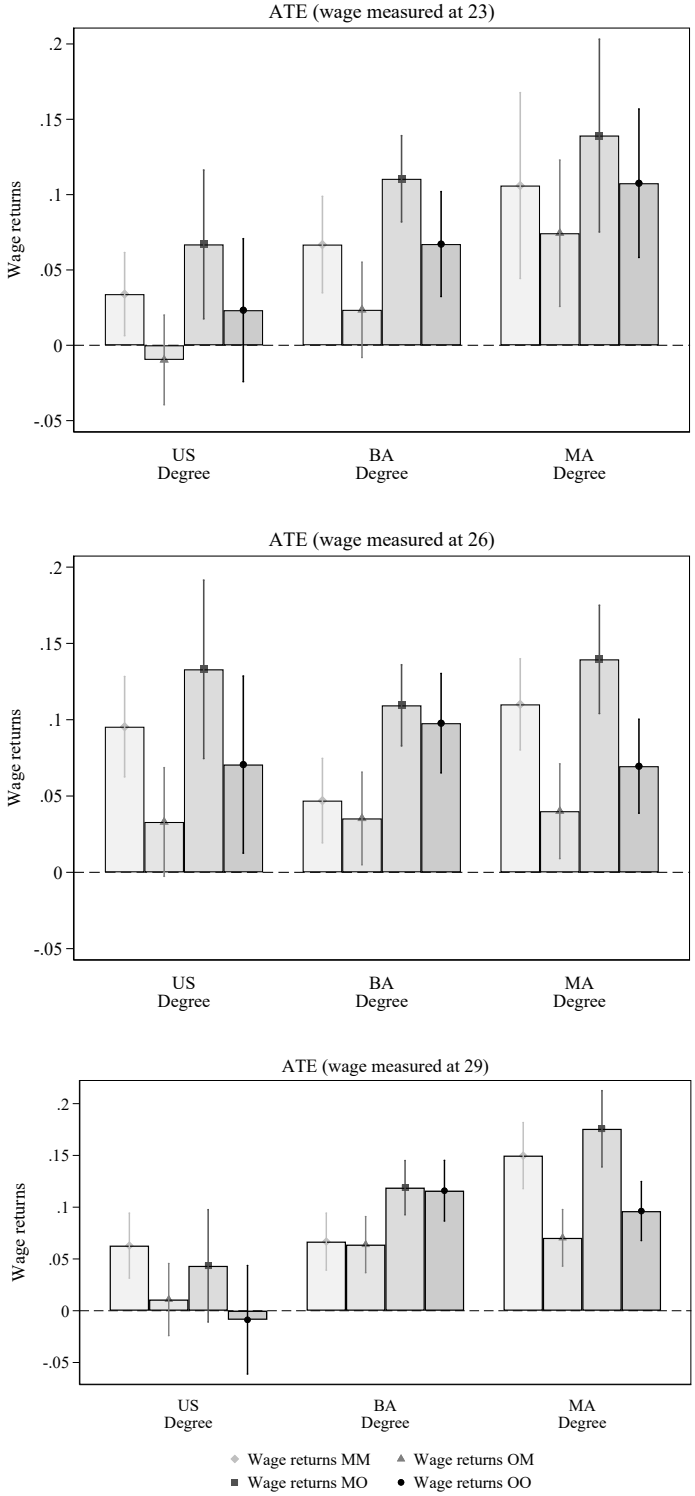
In Figure 5, we report the direct ATE on wages conditional on the match status at e and at e'. This delivers the following four conditional returns: (a) the wage return when adequately matched at both e and e' (Δ_{iae}^{MM}), (b) the wage return when overeducated at level e while adequately matched at level e' (Δ_{iae}^{OM}), (c) the wage return when adequately matched at e while overeducated at e' (Δ_{iae}^{MO}), and (d) the wage return when being overeducated at both e and e' (Δ_{iae}^{OO}). These conditional returns are reported for each of the three wage observations.

Δ_{iae}^{MM} increases by educational attainment. For instance, at age 23, Δ_{iae}^{MM} for an US, a BA, and an MA degree is 3.3%, 5.9%, and 9.3%, respectively. At age 29, these returns are 3.1%, 6.6%, and 10.6%. Also Δ_{iae}^{OM} is, in most cases, positive. Nonetheless, we find this return to be consistently lower than Δ_{iae}^{MM}. For instance, at age 29, the wage return to obtaining an MA degree (relative to a BA degree) is estimated to equal 7.0% when this additional investment leads to overeducation.

These two conditional returns are equivalent to the return to adequate education (a) and to overeducation (b), as reported in the overeducation literature. By subtracting these returns, we obtain the overeducation wage penalty, which is reported in Figure 6. At age 23, this penalty is estimated to be 4.2% and 4.1% at the US and BA level, respectively. Moreover, while the overeducation penalty for MA degrees is statistically insignificant at age 23, it increases to 8.7% by age 29. Conversely, for a BA degrees, this penalty nearly disappears by age 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 that initial overeducation generates a long-lasting scarring effect for US and MA graduates.

Investing in more education not only induces people to stay adequately educated or to become overeducated, it could improve their match status (case (c)) or induce them to stay overeducated (case (d)). As shown in Figure 5, also the returns conditional on these match statuses are usually positive. For instance, the return to an MA degree is still 9.6% at 29 for those who stay overeducated (Δ_{iae}^{OO}). And for those who improve their match status, it is even 17.5% (Δ_{iae}^{MO}). Moreover, while Δ_{iae}^{MO} comfortably exceeds Δ_{iae}^{MM} in most cases, Δ_{iae}^{OO} usually exceeds Δ_{iae}^{OM}. Henceforth, the standard measure of the return to overeducation (Δ_{iae}^{OM}) may provide an

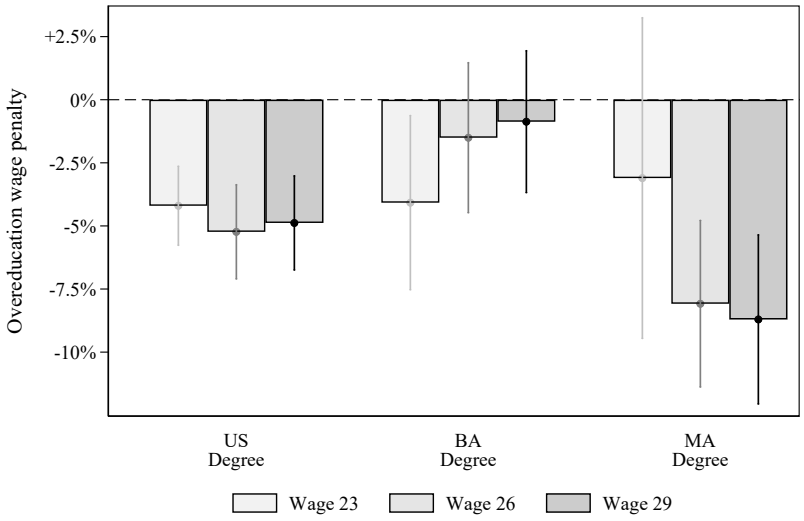
Figure 5: Conditional Returns (at 23, 26 and 29 years)



Notes: We simplify the notation from Equation 7 and we refer to the following: (i) Wage returns MM as Δ_{iae}^{MM} (a), (ii) Wage returns OM as Δ_{iae}^{OM} (b), (iii) Wage returns MO as Δ_{iae}^{MO} (c) and (iv) Wage returns OO as Δ_{iae}^{OO} (d). US, BA and MA indicate upper secondary degree, bachelor's degree, and master's degree, respectively.

underestimation of the actual return to education for those who are overeducated.

Figure 6: Overeducation Wage Penalty by Educational Attainment



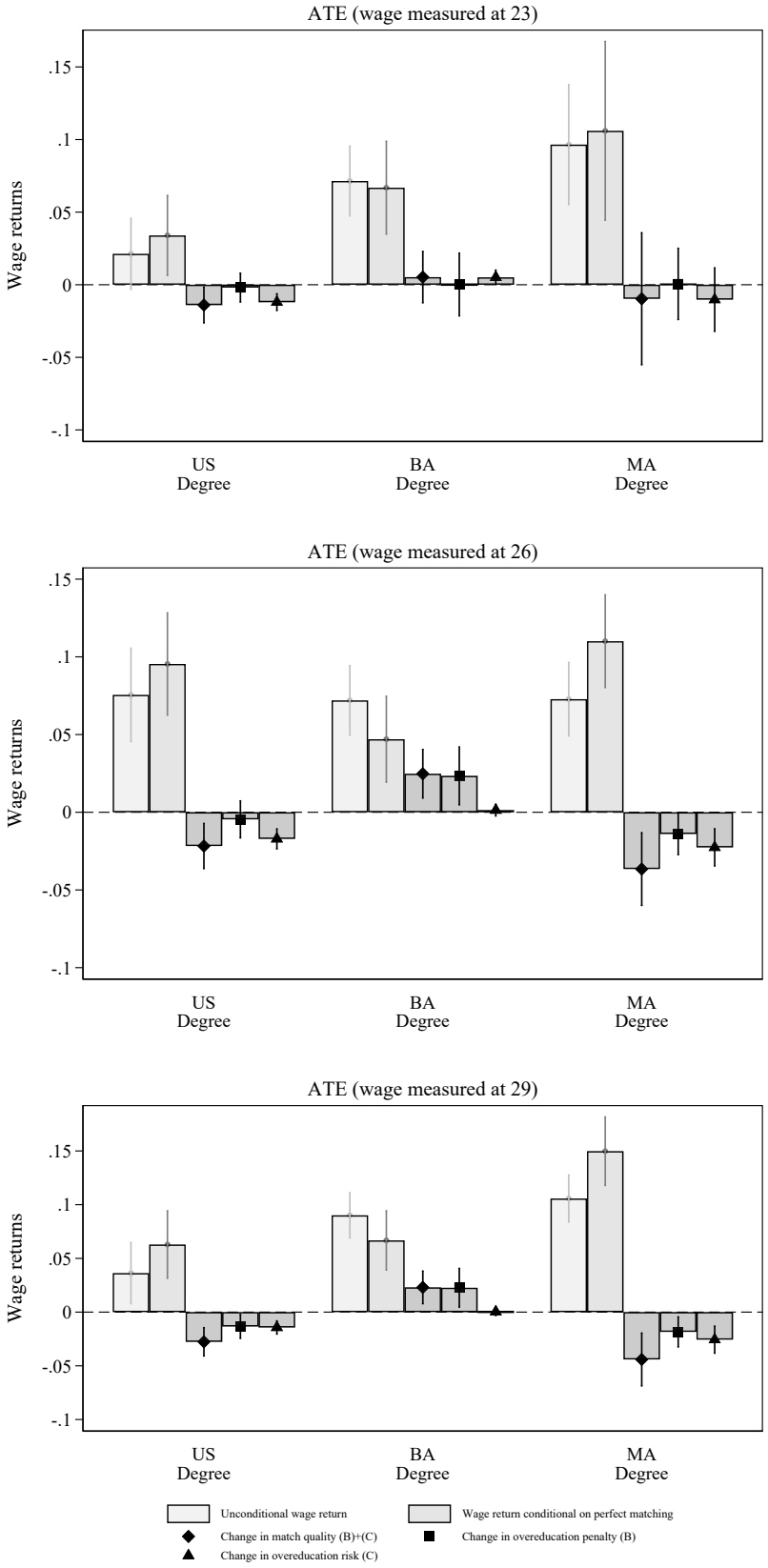
In Appendix C, we also report the results on these conditional returns while relying on our alternative treatment indicator ATE† and also considering the indirect effects of additional educational investments. Overall, our conclusions do not change when relying on these alternative definitions. The main differences pertain to the US level. Several of the conditional returns to US degrees are small and statistically insignificant when relying on the direct ATE definition. This is likely due to labor 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 substantial and statistically significant. This is consistent with the returns to US degrees being mainly indirect, as obtaining an US degree opens the door towards tertiary education.

6.3 Unconditional Returns: Decomposition

This paper offers a novel decomposition approach to investigate how overeducation affects the average unconditional wage return, as explained in Section 2. In Figure 7, we report these results for the direct ATEs. Figure 7 reports the unconditional return (Δ_{iae}), the return conditional on perfect matching (Δ_{iae}^{MM}), the component due to a change in match quality (Δ_{iae}^{Q}), and a further decomposition of the latter component based on whether it is due to a change in overeducation penalty or a change in overeducation risk.

While the unconditional wage returns to obtaining an MA degree are consistently positive,

Figure 7: Decomposition of Change in Match Quality



Notes: The decomposition approach is explained in more detail in Section 2 and represented by Equation 11. The unconditional wage return is Δ_{iae}, the wage return conditional on perfect matching is Δ_{iae}^{MM}, and the change in match quality component is Δ_{iae}^{Q}.

they are lower than those in the case of perfect matching. For instance, at age 29, the unconditional return equals 10.6% relative to a return of 14.9% in the case of perfect matching. In part (1.8 %-points), this is caused by the larger overeducation penalty for MA relative to BA degrees, while the remaining part (2.5 %-points) is attributable to the larger overeducation risk among MA graduates.

For BA graduates, the results are different, with their unconditional return being larger than the return conditional on perfect matching. Our decomposition suggests this is largely due to a reduced overeducation penalty for those with a BA degree relative to those with an US. Indeed, at age 26 and 29, the overeducation penalty for being overeducated as a worker with a BA degree is almost 0%.

Finally, regarding obtaining a US degree, the unconditional returns are lower but also less precise. Besides being the result of a low return in the case of perfect matching, this is due to a significant drop in match quality relative to when one would have entered the labor market without a US degree. For instance, at age 23, this drop in match quality is estimated to reduce the average unconditional return by approximately 1.3%-points.

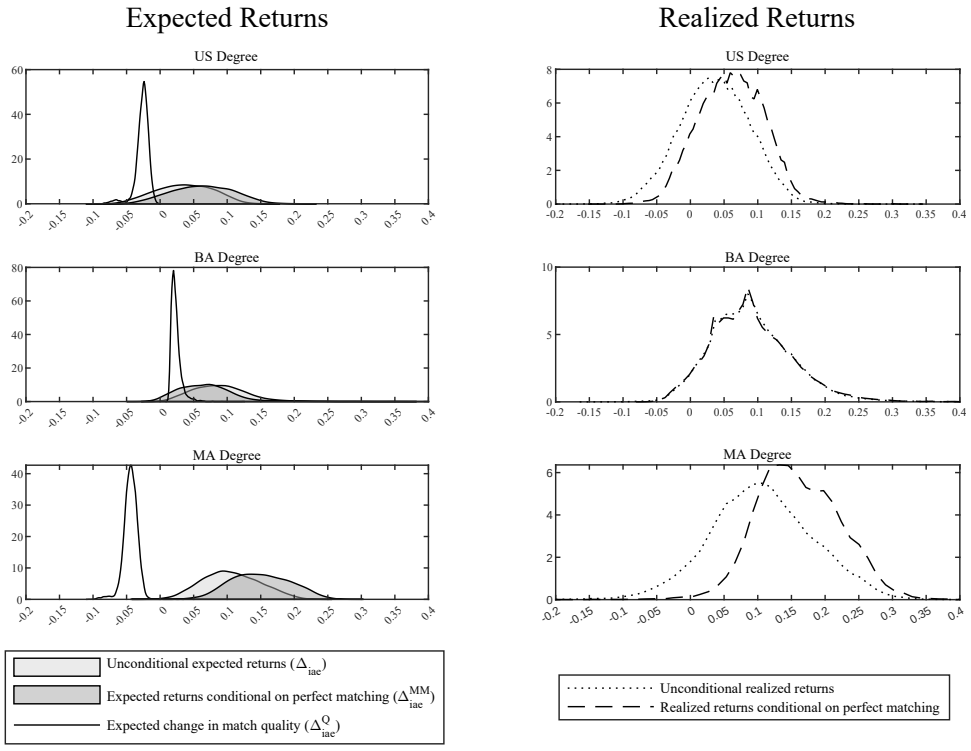
6.4 Heterogeneous Returns to Education

We also document whether the estimated effects are heterogeneous across individuals. First, we document the heterogeneity in the expected unconditional wage returns (Δ_{iae}), and its decomposition in the expected return conditional on perfect matching (Δ_{iae}^{MM}) and the expected wage component due to changes in match quality (Δ_{iae}^{Q}). These results are reported in the graphs on the left-hand side of Figure 8. We report results for each level of educational attainment and concentrate on ATE wage returns at age 29. The results for the other ages are reported in Appendix C.1.

We find substantial heterogeneity in both components of the unconditional return, albeit this heterogeneity is less pronounced for the change in match quality component (Δ_{iae}^{Q}) relative to the wage return conditional on perfect matching (Δ_{iae}^{MM}). Furthermore, in line with the results reported in the previous sections, we find the former to be negative for most individuals when obtaining a US or an MA degree, and positive when obtaining a BA degree.

As expected, we find the heterogeneity in these two components also translate into substantial heterogeneity in Δ_{iae}. Nonetheless, for each educational attainment, this heterogeneity is similar to the heterogeneity in returns conditional on perfect matching. This indicates that even

Figure 8: Simulated Distributions of Unconditional Wage Returns, Decomposition and Realized Returns (age 29)



if the differences in overeducation risk may reflect the heterogeneity in unconditional expected returns, they do not reinforce this heterogeneity. This is likely due to the fact that individuals with a high overeducation risk at a particular level of attainment also experience a higher risk of overeducation at lower levels of attainment.[20] Nonetheless, we find that overeducation affects the location of the distributions of unconditional returns. As a result of the negative Δ_{iae}^{Q}, we find that the distribution of Δ_{iae} is situated to the left of the distribution of Δ_{iae}^{MM}. However, Δ_{iae} remains substantial for most of the individuals. Finally, in line with the associated improvement in average match quality, we find that the Δ_{iae} for a BA degree exceeds its return conditional on perfect matching for most individuals.

Δ_{iae} partly depends on the difference in overeducation risk in educational attainment e relative to e'. However, depending on the match status at each level of attainment, realized (i.e., ex-post) returns may be lower or higher. Even if one has a high overeducation risk at e, one may still manage to be adequately matched due to idiosyncratic matching shocks (i.e., $\varepsilon_i^{oe} \neq 0$). To test for the impact of these idiosyncratic shocks, we simulate the distribution of two types of realized returns that emerge from a random matching process. The first distribution rep-

[20] As shown in Figure C2 in the Appendix, individuals with lower expected unconditional returns indeed usually experience a higher risk of overeducation across levels of educational attainment.

resents unconditional realized returns and is the one that emerges from a random matching process w.r.t. both overeducation in the first job and wages in later jobs. The second distribution, meanwhile, accounts for random matching w.r.t. wages in later jobs only while presuming perfect matching in the first job. The resulting distributions are reported in the graphs on the right-hand side of Figure 8.

As expected, the unconditional realized returns are much more heterogeneous than the unconditional expected returns. This is particularly the case for obtaining a BA and an MA degree. For instance, in the latter case, a substantial proportion of the individuals have a return conditional on random matching that is well above 10%. In contrast, others have negative realized returns. Importantly, this heterogeneity in realized returns for MA degrees is clearly less pronounced when we presume everyone to be perfectly matched in the first job and account for random matching with respect to wages in later jobs only. This aligns with the notion that overeducation is a source of heterogeneous realized returns to college, probably as a consequence of search and matching frictions.

6.5 Sensitivity Analyses

We perform several sensitivity analyses related to our model. First, we re-estimate the model based on each of the three separate overeducation measures and an alternative combined measure, as described in Section 4.4. As reported in Table 3 (Columns (1) to (6)), the direction and size of most of the estimated effects are very similar across the measures and in line with the benchmark results. This is in particular the case for the results on the overeducation penalty and the decomposition. There are just a few more marked differences with respect to the relationship between educational attainment and the overeducation probability. First, unlike the standard ISA (and all other individual) measures, the alternative ISAm measure delivers a positive effect of obtaining a BA on overeducation. However, it is reassuring that the results based on the alternative composite measure BMm, which accounts for measurement errors, remain very similar to those based on our standard BM. Second, we do not find a significant effect of obtaining an MA degree on overeducation when using the DSA measure. Overall, this highlights the need to account for measurement error as we do based our benchmark measure.

As a second sensitivity analysis, we test whether accounting for unobserved heterogeneity matters. We re-estimate our model while considering one heterogeneity type only or considering 4 heterogeneity types (see Table 3, columns (7) and (8)). The results based on a model

Table 3: Sensitivity Analysis on the Overeducation Measure and the Model

	Unobserved types (K):	With K=3:						With K=1:	With K=4:
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		Overeducation measure:							
	Educational attainment:	**BM**	BMm	ISA	ISAm	JA	DSA	BM	BM
(a) Effects of Educational Attainment on Overeducation									
ATE Direct	US	**0.274*** **	0.214***	0.272***	-0.010	0.242***	0.064**	0.265***	0.245***
		(0.023)	(0.028)	(0.026)	(0.028)	(0.027)	(0.029)	(0.023)	(0.021)
	BA	**-0.116*** **	-0.053**	-0.123***	0.061***	-0.055**	-0.153***	-0.126***	-0.092***
		(0.024)	(0.021)	(0.021)	(0.019)	(0.021)	(0.018)	(0.023)	(0.019)
	MA	**0.320*** **	0.128***	0.302***	0.448***	0.059*	-0.010	0.237***	0.306***
		(0.025)	(0.032)	(0.031)	(0.028)	(0.033)	(0.031)	(0.033)	(0.029)
(b) Overeducation Wage Penalty									
Wage 23	US	**-0.042*** **	-0.045***	-0.033***	-0.027***	-0.045***	-0.024***	-0.036***	-0.007
		(0.008)	(0.008)	(0.009)	(0.009)	(0.008)	(0.008)	(0.008)	(0.007)
	BA	**-0.041** **	-0.030**	-0.018	-0.010	-0.033**	-0.029*	-0.020	0.014
		(0.018)	(0.014)	(0.014)	(0.015)	(0.014)	(0.016)	(0.015)	(0.013)
	MA	**-0.031**	-0.022	-0.012	-0.012	-0.016	-0.086**	-0.014	0.001
		(0.032)	(0.037)	(0.034)	(0.034)	(0.036)	(0.036)	(0.032)	(0.030)
Wage 26	US	**-0.053*** **	-0.056***	-0.042***	-0.046***	-0.061***	-0.010	-0.033***	-0.069***
		(0.009)	(0.010)	(0.013)	(0.014)	(0.010)	(0.012)	(0.011)	(0.011)
	BA	**-0.015**	-0.017	-0.015	-0.020	-0.014	-0.052***	-0.014	-0.067***
		(0.015)	(0.013)	(0.018)	(0.019)	(0.013)	(0.018)	(0.015)	(0.016)
	MA	**-0.081*** **	-0.073***	-0.048**	-0.048**	-0.099***	-0.055***	-0.048*	-0.096***
		(0.017)	(0.016)	(0.021)	(0.023)	(0.015)	(0.020)	(0.024)	(0.021)
Wage 29	US	**-0.049*** **	-0.050***	-0.040***	-0.048***	-0.051***	-0.020*	-0.043***	-0.063***
		(0.010)	(0.010)	(0.011)	(0.014)	(0.010)	(0.012)	(0.012)	(0.011)
	BA	**-0.009**	-0.006	-0.015	-0.024	-0.003	-0.024	-0.018	-0.048***
		(0.014)	(0.012)	(0.014)	(0.016)	(0.012)	(0.016)	(0.015)	(0.013)
	MA	**-0.087*** **	-0.088***	-0.093***	-0.093***	-0.083***	-0.085***	-0.080***	-0.115***
		(0.017)	(0.017)	(0.020)	(0.022)	(0.016)	(0.020)	(0.023)	(0.022)
(c) Unconditional Wage Returns Decomposition (age 29)									
Δ_{iae}	US	**0.036** **	0.033**	0.018	0.013	0.033**	0.020	0.006	0.014
		(0.015)	(0.013)	(0.019)	(0.021)	(0.013)	(0.016)	(0.022)	(0.017)
	BA	**0.090*** **	0.091***	0.078***	0.078***	0.090***	0.081***	0.075***	0.078***
		(0.011)	(0.009)	(0.011)	(0.012)	(0.009)	(0.011)	(0.012)	(0.011)
	MA	**0.106*** **	0.156***	0.153***	0.136***	0.153***	0.154***	0.146***	0.144***
		(0.011)	(0.014)	(0.018)	(0.021)	(0.014)	(0.017)	(0.017)	(0.019)
Δ_{iae}^{MM}	US	**0.063*** **	0.050***	0.043**	0.017	0.055***	0.037**	0.032	0.045**
		(0.016)	(0.016)	(0.020)	(0.023)	(0.016)	(0.017)	(0.026)	(0.020)
	BA	**0.067*** **	0.061***	0.061***	0.073***	0.058***	0.078***	0.059***	0.065***
		(0.014)	(0.012)	(0.013)	(0.013)	(0.012)	(0.012)	(0.016)	(0.014)
	MA	**0.150*** **	0.201***	0.210***	0.197***	0.190***	0.177***	0.193***	0.198***
		(0.016)	(0.022)	(0.026)	(0.028)	(0.021)	(0.020)	(0.023)	(0.031)
Δ_{iae}^{Q}	US	**-0.028*** **	-0.017	-0.026***	-0.006	-0.023**	-0.017*	-0.028***	-0.033***
		(0.007)	(0.010)	(0.007)	(0.008)	(0.010)	(0.009)	(0.010)	(0.008)
	BA	**0.023*** **	0.027***	0.017**	0.005	0.029***	0.002	0.016*	0.015*
		(0.008)	(0.008)	(0.007)	(0.006)	(0.008)	(0.005)	(0.009)	(0.008)
	MA	**-0.044*** **	-0.048***	-0.056***	-0.059***	-0.038***	-0.023***	-0.047**	-0.059***
		(0.013)	(0.015)	(0.017)	(0.019)	(0.014)	(0.008)	(0.019)	(0.021)

Notes: Results using the benchmark model with unobserved heterogeneity (with K=3 unobserved types and with K=4 unobserved types) and without unobserved heterogeneity (with K=1 unobserved types). The overeducation measures represent respectively: the Benchmark Measure (BM), Job Analysis (JA), Indirect Self-Assessment (ISA) and Direct Self-Assessment (DSA). Educational attainment levels are coded as LS (lower secondary), US (upper secondary), BA (lower tertiary or Bachelor's degree), MA (higher tertiary or Master's degree). The measures used in the decomposition are the following: unconditional (ex-ante) wage returns (Δ_{iae}), wage return conditional on perfect matching (Δ_{iae}^{MM}) and change in match quality (Δ_{iae}^{Q}).

with 4 types are fairly similar, except for the strong overeducation penalty that is now found for the BA level as well. The model based on one type, meanwhile, suggest that not accounting for unobserved heterogeneity underestimates the overeducation wage penalty. Upon first glance, this seems surprising given that overeducated individuals are often thought to have less favorable traits. However, in addition to accounting for classical unobserved heterogeneity, our models also account for dynamic selection. For instance, as shown in Table B5 in Appendix B, individuals of Type 3, who enjoy the highest levels of educational achievement and lowest risk of being overeducated, are also more likely to be selected in the wage equations at ages 26 and 29. A likely explanation is that individuals with a lower overeducation risk are more inclined to take up jobs as the offered wages in these jobs are less likely to exceed their reservation wage. This causes the overeducation wage penalty to be underestimated in the model with only one type.

7 Conclusions

This paper offers a novel decomposition of returns to education based on overeducation risk and develops a dynamic model based on detailed longitudinal Belgian data that investigates the relationship between educational attainment, overeducation, and wages. This allows us to contribute to the literature in four main ways. First, our decomposition allows us to gauge the importance of overeducation risk in explaining wage returns to education more comprehensively. Second, we contribute to the discussion on whether the relationship between overeducation and wages is causal. Third, we investigate the underexplored question of whether obtaining a college degree increases the likelihood of being overeducated. Finally, we also explore how overeducation is a channel that generates both heterogeneous expected and realized returns

Our results suggest that being overeducated in the first job generates a significantly negative and persistent wage penalty. At age 23, this penalty ranges from around 4% for an upper secondary or a bachelor's degree to approximately 3% for a master's degree. Overall, this confirms the findings of the literature on this topic (Hartog, 2000; McGuinness, 2006; Leuven & Oosterbeek, 2011; Barnichon & Zylberberg, 2019). However, relative to the literature, we also show that the overeducation penalty for a master's degree increases over time, with an 8.7% penalty at age 29, while the penalty for a bachelor's degree fades away at age 29. At the same time, the overeducation wage penalty for an upper secondary education degree remains

consistent until age 29.

Nevertheless, our novel decomposition approach reveals that this penalty generates a misleading picture of the importance of overeducation in explaining wage returns to education. Indeed, the unconditional return is affected by the change in overeducation penalty and overeducation risk when investing in more education rather than by the overeducation penalty and risk levels per se. In fact, concerning a bachelor's degree, we find evidence that the unconditional wage return to education exceeds the return conditional on perfect matching. This is partly due to our finding that a bachelor's degree (relative to an upper secondary degree) reduces overeducation risk. Moreover, for master's degrees, the impact of overeducation on its unconditional return seems moderate at best. Although master's degrees are associated with a reduced match quality relative to bachelor's degrees (but not to upper secondary degrees), their unconditional return is still substantial. The unconditional return to an upper secondary degree, meanwhile, is found to be much more limited due to, among other things, the increased overeducation risk and penalty. Overall, these findings do not suggest that overeducation indicates considerable overinvestment in higher education. Instead, they are consistent with a polarized labor market (cf. Autor et al., 2003; Goos et al., 2009) in which obtaining a higher education degree may be a viable way to avoid overeducation.

Obtaining a higher education degree does not always guarantee a positive wage return. Indeed, in line with several other studies (e.g. Arcidiacono, 2004; Rodríguez et al., 2016), we find the heterogeneity in returns to be substantial. Overall, we find that while differences in overeducation probabilities may reflect differences in unconditional wage returns across individuals (e.g. due to differences in abilities), overeducation is not a channel that further reinforces this heterogeneity. Indeed, even if individuals are more likely to be overeducated, obtaining a college degree may still improve their chances of obtaining a medium-skilled job (cf. Verhaest et al., 2018) and generate a substantial wage return. As an explanation for heterogeneous realized (ex-post) returns for education, meanwhile, overeducation seems to be a more significant driver. By simulating a random matching process w.r.t. both overeducation in the first job and wages in later jobs, we find the wage returns conditional on this random matching to be negative for a substantial percentage of the graduates despite their positive unconditional (ex-ante) return. Moreover, for master's degrees, this heterogeneity in ex-post returns is much less pronounced when presuming random matching with respect to wages only. This is consistent with the notion that overeducation results, at least partly, from labor market frictions (cf. Gautier,

2002; Dolado et al., 2009) and that investing in higher education is a risky venture (cf. Leuven and Oosterbeek, 2011).

These results have important policy implications. First, they suggest that reducing investments in higher education may not be the right answer for solving overeducation among young workers. On the contrary, widening access to bachelor's degree programs may even be beneficial. Second, rather than viewing overeducation as indicative of inefficient educational policies, our findings suggest that it is more fruitful to focus on labor market policies that reduce frictions. Reducing these frictions may not only diminish the risk of overeducation at the start of the career but may also minimize the scarring effects of this initial mismatch.

We end by indicating some directions for further research. First, our analysis is based on data from the early nineties to the first years of the new century. While this a period for which job polarization has been well documented (Goos et al., 2009), participation in higher education has only continued to increase. Relying on more recent data would therefore be interesting. Second, the Belgian labor market is known to be relatively rigid. Besides being associated with stronger overeducation penalties (Levels et al., 2014), the context of a rigid labor market is also associated with stronger scarring effects in the case of a bad labor market entry (Cockx and Ghirelli, 2016). Estimating a similar model while relying on data from a more flexible labor market context would provide another interesting avenue for further research. Finally, by focusing on obtaining a higher level of education, we only account 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 programs and institutions (Robst, 1995; Verhaest and van der Velden, 2013). It would be interesting to extend our model by accounting for this more qualitative dimension of investment in education.

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A Data

To ensure the estimated model remains tractable, we remove from the initial sample those individuals (i) who experienced more than one year of delay at the start of their primary education (76 individuals) and (ii) those who have special needs that are catered for in schools providing special care (124 individuals). Moreover, we remove another 638 individuals with (iii) inconsistent, erroneous, or incomplete data regarding the exogenous variables (cf. infra) and their educational careers (see Table A1 in Appendix). This leaves us with a final sample of 8,162 individuals, which is used to estimate the equations related to the educational outcomes.

To estimate the equation related to the overeducation status in the first jobs, the sample is further reduced to 7,211 individuals. This is because there are 701 individuals for whom we have no data regarding a first job (either because they did not participate in the follow-up survey(s) or because they did not have a first job by age 29) and another 250 for whom the data on overeducation is missing.

Moreover, 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). Due to missing data, the number of observations in the wage equations drops to 4,407, 3,379, and 3,142 for the ages 23, 26, and 29, respectively. Concerning age 23, data is missing for two main 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 wages at age 23. In particular, for the 1978 and 1980 cohorts, those who were still in a first job that had started within the last year were precluded from answering these questions, while for the 1976 cohort, none of the individuals who were still in their first job (irrespective of when it started) were asked to indicate their wage. For age 26 and age 29, meanwhile, missing data on wages are primarily caused by a lack of surveying (for the 1978 cohort at age 26 and the 1980 cohort at age 29) or due to attrition. Missing data due to respondents' refusal to answer or because of wage outliers are less important for each of the three measurement points. As these missing data are unlikely to be random, we account for this in our analysis by adding three selection equations to our model.

A.1 Descriptive Statistics for Overeducation

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**

Table A2: ISCO-08 Occupations and Overeducation (at least 30 individuals)

ISCO-08	**JA**	**ISA**	**ISAm**	**DSA**	**LF**	**LFm**
Total	0.52	0.41	0.31	0.28	0.44	0.52
Shelf Fillers	0.97	0.92	0.92	0.67	0.95	0.95
Hand Packers	0.88	0.79	0.87	0.55	0.83	0.87
Window Cleaners	0.82	0.82	0.82	0.64	0.82	0.82
Shop Sales Assistants	0.82	0.82	0.15	0.42	0.82	0.82
Freight Handlers	0.93	0.71	0.71	0.61	0.80	0.91
Product Graders and Testers (except Foods and Beverages)	0.87	0.65	0.70	0.65	0.80	0.89
Cashiers and Ticket Clerks	0.81	0.81	0.81	0.61	0.79	0.79
Waiters	0.78	0.78	0.23	0.52	0.78	0.78
Dairy Products Makers	0.76	0.76	0.10	0.34	0.76	0.76
Kitchen Helpers	0.73	0.73	0.73	0.32	0.73	0.73
...						
Accounting Associate Professionals	0.44	0.10	0.10	0.18	0.15	0.43
Cooks	0.14	0.14	0.12	0.14	0.14	0.14
Motor Vehicle Mechanics and Repairers	0.12	0.12	0.12	0.11	0.12	0.12
Cement, Stone and Other Mineral Products Machine Operators	0.70	0.00	0.00	0.12	0.12	0.67
Town and Traffic Planners	0.10	0.10	0.10	0.07	0.10	0.10
Secondary Education Teachers	0.02	0.09	0.09	0.03	0.09	0.09
Nursing Associate Professionals	0.21	0.03	0.03	0.02	0.03	0.21
Beauticians and Related Workers	0.11	0.01	0.01	0.01	0.01	0.11
Specialist Medical Practitioners	0.00	0.00	0.00	0.03	0.00	0.00
Lawyers	0.00	0.00	0.00	0.08	0.00	0.00

Notes: Overeducation measures are coded as JA (Job Analysis), ISA (Indirect Self-Assessment), ISAm (Indirect Self-Assessment Median), DSA (Direct Self-Assessment), RM (Realized Matches), Benchmark Measure (BM), Benchmark Measure Median (BMm). Table including occupations with, at least, 30 individuals classified as such.

B Model

In Table B3, we gradually add unobserved heterogeneity types (K) to the model and we re-estimate it starting from different starting values. Using AIC and BIC, together with looking at the types fraction within the sample, we select the model with 3 heterogeneity types. This is because the model with 5 K fails to converge, and the model with 4 K consistently has one of the types with less than a 2% fraction.

Table B3: Model selection

	K			
	2	3	4	5
Log-likelihood	37857.07	**37756.93**	36706.45	-
AIC	76910.15	**76749.87**	74688.9	-
BIC	81100.48	**81080.34**	79159.52	-

B.1 Counterfactual Simulation

To gauge the treatment effects of interest and their confidence intervals, we rely on a counterfactual simulation strategy (Cockx et al., 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 randomly assign a heterogeneity type to each individual in the sample. Thereafter, based on this novel set of parameters, we simulate the full sequence of schooling and labor 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 shown in Table B4. In most cases, the observed probabilities fall within the 95% confidence bounds of the simulated probabilities. Thus, the model fits the observed outcomes in the dataset relatively well.

A similar simulation strategy is adopted to gauge the composition of the three heterogeneity types. Table B5 displays the simulated outcomes when forcing all individuals to be in 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 (relative to Type 3 individuals) a higher probability of experiencing a delay at the start of primary and secondary education, a lower

Table B4: Goodness of fit

Variables	**Data**	Simulation	95% CI	
(a) Delays:				
Delay (Start Primary Education)	**0.015**	0.016	0.012	0.020
Delay (Start Secondary Education)	**0.101**	0.104	0.095	0.113
(b) Educational Choices:				
Start and Track Choice in LS	**2.515**	2.510	2.496	2.525
LS Degree	**0.963**	0.961	0.955	0.967
Start and Track Choice in US	**2.445**	2.442	2.427	2.457
US Degree	**0.946**	0.945	0.938	0.952
Start and Track Choice in BA	**1.958**	1.955	1.934	1.977
BA Degree	**2.112**	2.052	2.022	2.083
Start and Track Choice in MA	**1.755**	1.723	1.684	1.761
MA Degree	**2.608**	2.611	2.550	2.672
(c) Labor market outcomes:				
Overeducation	**0.456**	0.455	0.439	0.472
Wage Selection at 23	**0.584**	0.584	0.570	0.598
Log-hourly wage at 23	**1.973**	1.969	1.962	1.975
Wage Selection at 26	**0.450**	0.420	0.409	0.431
Log-hourly wage at 26	**2.070**	2.063	2.056	2.070
Wage Selection at 29	**0.424**	0.389	0.379	0.399
Log-hourly wage at 29	**2.124**	2.118	2.110	2.126

Notes: Educational attainment levels are coded as LS (lower secondary), US (upper secondary), BA (lower tertiary or Bachelor's degree), MA (higher tertiary or Master's degree). 95% CI indicated the 95 percent confidence intervals, as simulated using our approach.

probability of completing 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, who are much less prevalent in the data, seem to form a more specific category, as they combine a high probability of overeducation with high wages.

Table B5: Probability types simulated models

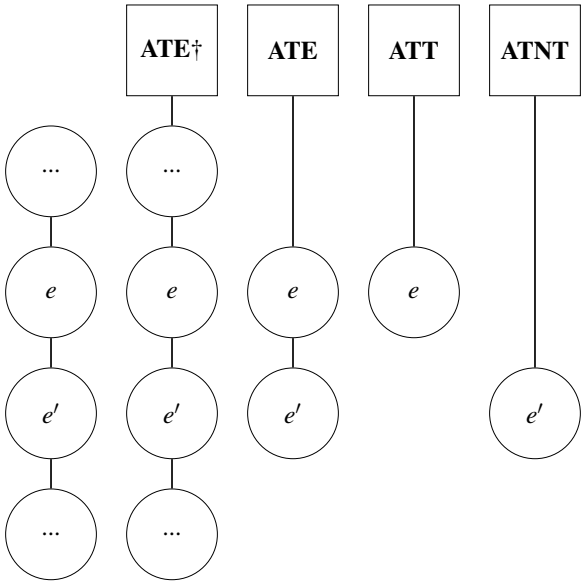
Variables	**Overall**	Type 1	Type 2	Type 3
		76.41%	4.44%	19.15%
(a) Delays:				
Delay in Primary Education	0.016	0.015	0.024	0.016
Delay in Secondary Education	0.104	0.105	0.079	0.076
(b) Educational Choices:				
Start and Track Choice in LS	2.510	2.491	2.568	2.579
LS Degree	0.961	0.958	0.970	0.976
Start and Track Choice in US	2.442	2.414	2.486	2.507
US Degree	0.945	0.949	0.925	0.951
Start and Track Choice in BA	1.955	1.925	2.034	2.051
BA Degree	2.052	2.027	2.063	2.135
Start and Track Choice in MA	1.723	1.669	2.024	1.749
MA Degree	2.611	2.604	2.484	2.682
(c) Labor market outcomes:				
Overeducation	0.455	0.457	0.619	0.389
Wage Selection at 23	0.584	0.602	0.604	0.492
Log-hourly wage at 23	1.969	1.963	2.186	1.960
Wage Selection at 26	0.420	0.264	0.956	0.920
Log-hourly wage at 26	2.063	2.041	2.406	2.050
Wage Selection at 29	0.389	0.235	0.695	0.926
Log-hourly wage at 29	2.118	2.098	2.618	2.279

Notes: Educational attainment levels are coded as LS (lower secondary), US (upper secondary), BA (lower tertiary or Bachelor's degree), MA (higher tertiary or Master's degree).

B.2 Treatment Effects

As in Heckman et al. (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 perspective because dynamic selection does not result in everyone having a reasonable likelihood of reaching 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 of being overeducated and for the wage returns related to an MA, we compute the treatment effect over those who obtained either a BA or an MA as their maximum level of educational attainment.

Figure B1: Definition of treatment effects



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

Moreover, 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 obtains an MA, ATT for those that obtained an MA, and ATNT for those with a BA only). The difference between the

ATT and the ATE is a measure of sorting on gains, while the difference between the ATNT and the ATE is a measure of sorting on losses (Heckman et al., 2018a, 2018b). These definitions are summarised in Figure B1, where e represents the treatment level of educational attainment and e' represents one level below this treatment level (e.g., if e is college, e' is upper secondary). The circles indicate which part of the sample is taken into account for the calculation of each of the treatment effects.

Finally, in addition to differentiating between ATE†s and ATEs, we also differentiate between direct ATEs and total ATEs, with total ATEs also taking into account that a certain level of educational attainment enables an individual to enroll in programs at higher levels of educational attainment and, thereby, generate indirect effects.

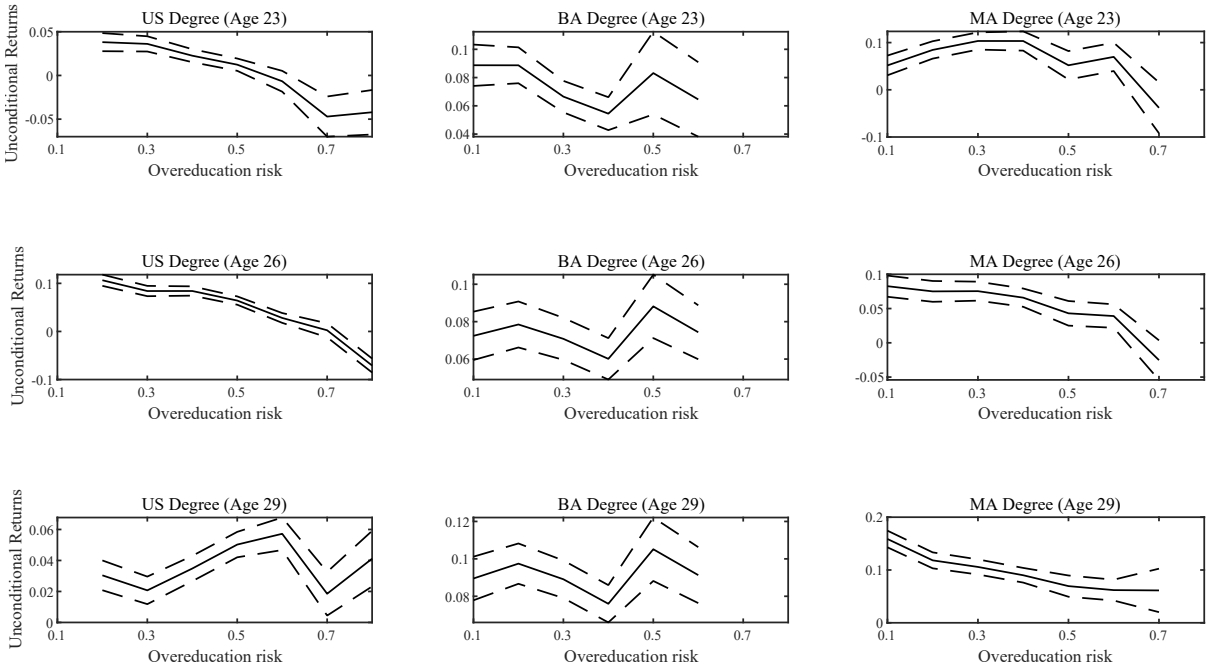
C Treatment Effects Tables

Table C6: Impact of Educational Attainment e Relative to Different Base Levels e'

	Impact of e:	**US**	**BA**		**MA**		
	Relative to:	LS	LS	US	LS	US	BA
ATE†	Direct	0.305***	0.214***	-0.091***	0.478***	0.173***	0.283***
		(0.017)	(0.019)	(0.018)	(0.024)	(0.023)	(0.025)
	Total	0.302***	0.297***	-0.008	0.478***	0.173***	0.283***
		(0.016)	(0.018)	(0.016)	(0.024)	(0.023)	(0.025)
ATE	Direct	0.332***	0.225***	-0.089***	0.484***	0.187***	0.292***
		(0.016)	(0.019)	(0.018)	(0.027)	(0.026)	(0.023)
	Total	0.310***	0.284***	-0.028	0.484***	0.187***	0.292***
		(0.016)	(0.019)	(0.017)	(0.027)	(0.026)	(0.023)

Notes: ATE† includes all individuals in the sample, while ATE only selects individuals who attained either e or e'. Total includes the effect of enrolling in higher educational attainment rather than e, while direct only includes the effect of educational attainment e.

Figure C2: Expected Unconditional Returns and Risk of Overeducation across Levels of Educational Attainment (Ages 23, 26 and 29)



Notes: This figure shows the correlation between the individual's overeducation risk and the relative expected unconditional returns across levels of educational attainment. Overeducation risk is between 0 and 1, with 1 being overeducated with 100% probability. Educational attainment levels are US Degree (Upper Secondary Education), BA Degree (Bachelor's Degree), and MA Degree (Master's Degree). Generally, individuals with a higher risk of overeducation have lower expected unconditional returns. The correlation is only unclear for BA Degrees. However, overall, it suggests that these individuals have very similar returns across the overeducation risk distribution. This could be partially attributed to the fact that BA degree attainment has large negative effects on the probability of being overeducated. Therefore, individuals with a larger risk of overeducation might benefit from this in terms of returns. Dashed lines represent 95 confidence intervals.

Table C7: Wage returns treatment effects: Direct effects

		Direct effects											
		ATE†			ATE			ATT			ATNT		
		US	BA	MA	US	BA	MA	US	BA	MA	US	BA	MA
Wage 23	AM-AM	0.034**	0.067***	0.106***	0.029**	0.069***	0.097***	0.030**	0.070***	0.088***	0.024*	0.069***	0.103***
		(0.014)	(0.016)	(0.031)	(0.013)	(0.015)	(0.030)	(0.013)	(0.012)	(0.026)	(0.013)	(0.019)	(0.034)
	AM-OE	-0.010	0.024	0.074***	-0.013	0.028*	0.066***	-0.013	0.037***	0.039*	-0.017	0.023	0.084***
		(0.015)	(0.016)	(0.025)	(0.013)	(0.015)	(0.022)	(0.013)	(0.013)	(0.022)	(0.013)	(0.019)	(0.026)
	OE-AM	0.067***	0.110***	0.139***	0.061**	0.112***	0.136***	0.062**	0.114***	0.136***	0.053**	0.111***	0.136***
		(0.025)	(0.015)	(0.033)	(0.024)	(0.013)	(0.029)	(0.024)	(0.012)	(0.028)	(0.024)	(0.017)	(0.034)
	OE-OE	0.023	0.067***	0.108***	0.018	0.071***	0.105***	0.019	0.081***	0.087***	0.013	0.065***	0.117***
		(0.024)	(0.018)	(0.025)	(0.024)	(0.016)	(0.024)	(0.024)	(0.014)	(0.023)	(0.023)	(0.020)	(0.027)
	Obs (Dir.)	0.021*	0.071***	0.097***	0.016	0.074***	0.089***	0.017	0.078***	0.070***	0.010	0.072***	0.102***
		(0.012)	(0.012)	(0.021)	(0.011)	(0.011)	(0.019)	(0.011)	(0.009)	(0.018)	(0.011)	(0.014)	(0.022)
	Obs	0.068***	0.104***	0.097***	0.045***	0.100***	0.089***	0.047***	0.093***	0.070***	0.029**	0.104***	0.102***
		(0.013)	(0.012)	(0.021)	(0.012)	(0.011)	(0.019)	(0.012)	(0.009)	(0.018)	(0.011)	(0.014)	(0.022)
Wage 26	AM-AM	0.095***	0.047***	0.110***	0.091***	0.050***	0.121***	0.093***	0.057***	0.109***	0.079***	0.046***	0.129***
		(0.017)	(0.014)	(0.015)	(0.016)	(0.013)	(0.016)	(0.016)	(0.011)	(0.015)	(0.016)	(0.016)	(0.018)
	AM-OE	0.033*	0.035**	0.040**	0.038**	0.035**	0.040***	0.039**	0.018	0.062***	0.033**	0.047***	0.026
		(0.018)	(0.015)	(0.016)	(0.016)	(0.015)	(0.014)	(0.017)	(0.014)	(0.014)	(0.016)	(0.017)	(0.017)
	OE-AM	0.133***	0.109***	0.140***	0.120***	0.111***	0.154***	0.123***	0.128***	0.131***	0.101***	0.101***	0.168***
		(0.030)	(0.014)	(0.018)	(0.029)	(0.013)	(0.018)	(0.029)	(0.012)	(0.019)	(0.028)	(0.016)	(0.020)
	OE-OE	0.071**	0.098***	0.070***	0.067**	0.096***	0.073***	0.069**	0.089***	0.084***	0.055*	0.101***	0.066***
		(0.030)	(0.017)	(0.016)	(0.029)	(0.016)	(0.017)	(0.029)	(0.014)	(0.016)	(0.028)	(0.018)	(0.019)
	Obs (Dir.)	0.076***	0.072***	0.073***	0.073***	0.074***	0.078***	0.075***	0.076***	0.086***	0.061***	0.073***	0.073***
		(0.015)	(0.011)	(0.012)	(0.014)	(0.011)	(0.012)	(0.014)	(0.009)	(0.011)	(0.014)	(0.013)	(0.014)
	Obs	0.122***	0.109***	0.073***	0.102***	0.104***	0.078***	0.106***	0.095***	0.086***	0.082***	0.110***	0.073***
		(0.015)	(0.010)	(0.012)	(0.014)	(0.009)	(0.012)	(0.014)	(0.009)	(0.011)	(0.014)	(0.011)	(0.014)
Wage 29	AM-AM	0.063***	0.067***	0.150***	0.067***	0.069***	0.162***	0.066***	0.073***	0.158***	0.075***	0.067***	0.165***
		(0.016)	(0.014)	(0.016)	(0.015)	(0.013)	(0.016)	(0.015)	(0.011)	(0.015)	(0.015)	(0.016)	(0.019)
	AM-OE	0.011	0.064***	0.070***	0.018	0.061***	0.075***	0.017	0.041***	0.111***	0.027*	0.073***	0.052***
		(0.018)	(0.014)	(0.014)	(0.016)	(0.013)	(0.013)	(0.016)	(0.013)	(0.014)	(0.016)	(0.016)	(0.016)
	OE-AM	0.043	0.119***	0.176***	0.044*	0.121***	0.182***	0.043	0.128***	0.159***	0.051*	0.116***	0.197***
		(0.028)	(0.013)	(0.019)	(0.027)	(0.013)	(0.017)	(0.027)	(0.012)	(0.018)	(0.027)	(0.015)	(0.020)
	OE-OE	-0.009	0.116***	0.096***	-0.005	0.112***	0.095***	-0.006	0.096***	0.111***	0.003	0.122***	0.084***
		(0.027)	(0.015)	(0.015)	(0.026)	(0.014)	(0.015)	(0.026)	(0.013)	(0.015)	(0.026)	(0.016)	(0.017)
	Obs (Dir.)	0.036**	0.090***	0.106***	0.040***	0.091***	0.111***	0.039***	0.086***	0.127***	0.046***	0.093***	0.101***
		(0.015)	(0.011)	(0.011)	(0.013)	(0.010)	(0.011)	(0.013)	(0.009)	(0.011)	(0.013)	(0.012)	(0.013)
	Obs	0.099***	0.138***	0.106***	0.077***	0.128***	0.111***	0.078***	0.113***	0.127***	0.071***	0.137***	0.101***
		(0.015)	(0.009)	(0.011)	(0.013)	(0.009)	(0.011)	(0.013)	(0.008)	(0.011)	(0.013)	(0.011)	(0.013)

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

Table C8: Wage returns treatment effects: Total effects

		Total effects											
		ATE†			ATE			ATT			ATNT		
		US	BA	MA	US	BA	MA	US	BA	MA	US	BA	MA
Wage 23	AM-AM	0.082***	0.107***	0.106***	0.058***	0.101***	0.097***	0.060***	0.089***	0.088***	0.042***	0.108***	0.103***
		(0.015)	(0.017)	(0.031)	(0.013)	(0.016)	(0.030)	(0.014)	(0.012)	(0.026)	(0.013)	(0.019)	(0.034)
	AM-OE	0.040***	0.063***	0.074***	0.016	0.059***	0.066***	0.018	0.056***	0.039*	0.003	0.062***	0.084***
		(0.014)	(0.014)	(0.025)	(0.013)	(0.013)	(0.022)	(0.013)	(0.012)	(0.022)	(0.013)	(0.017)	(0.026)
	OE-AM	0.115***	0.150***	0.139***	0.090***	0.144***	0.136***	0.093***	0.133***	0.136***	0.072***	0.151***	0.136***
		(0.025)	(0.015)	(0.033)	(0.024)	(0.014)	(0.029)	(0.024)	(0.013)	(0.028)	(0.024)	(0.018)	(0.034)
	OE-OE	0.073***	0.107***	0.108***	0.048**	0.103***	0.105***	0.051**	0.100***	0.087***	0.033	0.105***	0.117***
		(0.025)	(0.016)	(0.025)	(0.024)	(0.015)	(0.024)	(0.024)	(0.013)	(0.023)	(0.023)	(0.018)	(0.027)
	Obs (Dir.)	0.021*	0.071***	0.097***	0.016	0.074***	0.089***	0.017	0.078***	0.070***	0.010	0.072***	0.102***
		(0.012)	(0.012)	(0.021)	(0.011)	(0.011)	(0.019)	(0.011)	(0.009)	(0.018)	(0.011)	(0.014)	(0.022)
	Obs	0.068***	0.104***	0.097***	0.045***	0.100***	0.089***	0.047***	0.093***	0.070***	0.029**	0.104***	0.102***
		(0.013)	(0.012)	(0.021)	(0.012)	(0.011)	(0.019)	(0.012)	(0.009)	(0.018)	(0.011)	(0.014)	(0.022)
Wage 26	AM-AM	0.135***	0.091***	0.110***	0.115***	0.085***	0.121***	0.118***	0.081***	0.109***	0.096***	0.088***	0.129***
		(0.017)	(0.013)	(0.015)	(0.016)	(0.012)	(0.016)	(0.016)	(0.011)	(0.015)	(0.016)	(0.015)	(0.018)
	AM-OE	0.091***	0.067***	0.040**	0.075***	0.062***	0.040***	0.078***	0.037***	0.062***	0.059***	0.078***	0.026
		(0.017)	(0.013)	(0.016)	(0.016)	(0.012)	(0.014)	(0.016)	(0.013)	(0.014)	(0.016)	(0.015)	(0.017)
	OE-AM	0.173***	0.153***	0.140***	0.143***	0.146***	0.154***	0.148***	0.152***	0.131***	0.117***	0.142***	0.168***
		(0.029)	(0.012)	(0.018)	(0.028)	(0.012)	(0.018)	(0.028)	(0.012)	(0.019)	(0.029)	(0.014)	(0.020)
	OE-OE	0.129***	0.130***	0.070***	0.104***	0.123***	0.073***	0.107***	0.108***	0.084***	0.080***	0.132***	0.066***
		(0.030)	(0.014)	(0.016)	(0.029)	(0.014)	(0.017)	(0.029)	(0.013)	(0.016)	(0.029)	(0.015)	(0.019)
	Obs (Dir.)	0.076***	0.072***	0.073***	0.073***	0.074***	0.078***	0.075***	0.076***	0.086***	0.061***	0.073***	0.073***
		(0.015)	(0.011)	(0.012)	(0.014)	(0.011)	(0.012)	(0.014)	(0.009)	(0.011)	(0.014)	(0.013)	(0.014)
	Obs	0.122***	0.109***	0.073***	0.102***	0.104***	0.078***	0.106***	0.095***	0.086***	0.082***	0.110***	0.073***
		(0.015)	(0.010)	(0.012)	(0.014)	(0.009)	(0.012)	(0.014)	(0.009)	(0.011)	(0.014)	(0.011)	(0.014)
Wage 29	AM-AM	0.122***	0.125***	0.150***	0.102***	0.115***	0.162***	0.102***	0.107***	0.158***	0.097***	0.120***	0.165***
		(0.016)	(0.013)	(0.016)	(0.015)	(0.012)	(0.016)	(0.015)	(0.011)	(0.015)	(0.015)	(0.015)	(0.019)
	AM-OE	0.080***	0.103***	0.070***	0.059***	0.091***	0.075***	0.060***	0.065***	0.111***	0.054***	0.107***	0.052***
		(0.016)	(0.012)	(0.014)	(0.015)	(0.012)	(0.013)	(0.015)	(0.012)	(0.014)	(0.015)	(0.014)	(0.016)
	OE-AM	0.103***	0.177***	0.176***	0.079***	0.166***	0.182***	0.080***	0.162***	0.159***	0.074***	0.169***	0.197***
		(0.027)	(0.012)	(0.019)	(0.026)	(0.012)	(0.017)	(0.026)	(0.012)	(0.018)	(0.026)	(0.014)	(0.020)
	OE-OE	0.060**	0.155***	0.096***	0.037	0.142***	0.095***	0.038	0.121***	0.111***	0.030	0.156***	0.084***
		(0.027)	(0.013)	(0.015)	(0.026)	(0.012)	(0.015)	(0.026)	(0.012)	(0.015)	(0.026)	(0.014)	(0.017)
	Obs (Dir.)	0.036**	0.090***	0.106***	0.040***	0.091***	0.111***	0.039***	0.086***	0.127***	0.046***	0.093***	0.101***
		(0.015)	(0.011)	(0.011)	(0.013)	(0.010)	(0.011)	(0.013)	(0.009)	(0.011)	(0.013)	(0.012)	(0.013)
	Obs	0.099***	0.138***	0.106***	0.077***	0.128***	0.111***	0.078***	0.113***	0.127***	0.071***	0.137***	0.101***
		(0.015)	(0.009)	(0.011)	(0.013)	(0.009)	(0.011)	(0.013)	(0.008)	(0.011)	(0.013)	(0.011)	(0.013)

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

Table C9: 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
US	-0.042***	-0.044***	-0.042***	-0.041***	-0.039***	-0.043***	-0.042***	-0.040***	-0.042***	-0.038***	-0.036***	-0.044***
	(0.008)	(0.007)	(0.007)	(0.007)	(0.008)	(0.008)	(0.007)	(0.008)	(0.007)	(0.009)	(0.010)	(0.009)
BA	-0.043**	-0.023*	-0.023*	-0.041***	-0.023*	-0.024**	-0.034***	-0.044***	-0.041***	-0.046**	-0.010	-0.012
	(0.017)	(0.013)	(0.012)	(0.016)	(0.013)	(0.012)	(0.012)	(0.010)	(0.010)	(0.021)	(0.016)	(0.015)
MA	-0.032	-0.070***	-0.079***	-0.031	-0.081***	-0.087***	-0.050*	-0.048***	-0.048***	-0.019	-0.103***	-0.113***
	(0.034)	(0.018)	(0.018)	(0.032)	(0.017)	(0.017)	(0.027)	(0.015)	(0.014)	(0.040)	(0.022)	(0.022)
	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
US	-0.044***	-0.062***	-0.052***	-0.042***	-0.052***	-0.049***	-0.043***	-0.054***	-0.049***	-0.039***	-0.044***	-0.047***
	(0.010)	(0.011)	(0.011)	(0.008)	(0.010)	(0.010)	(0.008)	(0.010)	(0.010)	(0.009)	(0.011)	(0.010)
BA	-0.043**	-0.012	-0.003	-0.041**	-0.015	-0.009	-0.033***	-0.039***	-0.032***	-0.046**	0.001	0.006
	(0.019)	(0.016)	(0.015)	(0.018)	(0.015)	(0.014)	(0.013)	(0.012)	(0.012)	(0.023)	(0.019)	(0.018)
MA	-0.032	-0.070***	-0.079***	-0.031	-0.081***	-0.087***	-0.050*	-0.048***	-0.048***	-0.019	-0.103***	-0.113***
	(0.034)	(0.018)	(0.018)	(0.032)	(0.017)	(0.017)	(0.027)	(0.015)	(0.014)	(0.040)	(0.022)	(0.022)

Table C10: Decomposition wage returns (Direct)

		Direct effects											
		ATE†			ATE			ATT			ATNT		
		US	BA	MA	US	BA	MA	US	BA	MA	US	BA	MA
Wage 23	Unconditional WR	0.021*	0.071***	0.097***	0.015	0.074***	0.089***	0.017	0.078***	0.070***	0.009	0.072***	0.102***
		(0.012)	(0.012)	(0.021)	(0.011)	(0.011)	(0.019)	(0.011)	(0.009)	(0.018)	(0.011)	(0.014)	(0.022)
	AM-AM	0.034**	0.067***	0.106***	0.028**	0.069***	0.097***	0.030**	0.070***	0.088***	0.022*	0.069***	0.103***
		(0.014)	(0.016)	(0.031)	(0.013)	(0.015)	(0.030)	(0.013)	(0.012)	(0.026)	(0.013)	(0.019)	(0.034)
	Difference	-0.013**	0.005	-0.009	-0.013**	0.005	-0.008	-0.013**	0.008	-0.018	-0.013*	0.004	-0.001
		(0.006)	(0.009)	(0.023)	(0.007)	(0.008)	(0.023)	(0.006)	(0.007)	(0.019)	(0.007)	(0.010)	(0.027)
	Change in match quality	-0.014**	0.005	-0.010	-0.014**	0.006	-0.007	-0.014**	0.009	-0.017	-0.013**	0.004	-0.001
		(0.006)	(0.009)	(0.023)	(0.006)	(0.008)	(0.023)	(0.006)	(0.007)	(0.019)	(0.006)	(0.009)	(0.027)
	Change in overeducation penalty	-0.002	0.000	0.001	-0.002	0.001	0.003	-0.002	0.005	-0.001	-0.002	-0.001	0.005
		(0.005)	(0.011)	(0.013)	(0.005)	(0.010)	(0.013)	(0.005)	(0.008)	(0.011)	(0.005)	(0.012)	(0.015)
	Change in overeducation risk	-0.012***	0.005**	-0.010	-0.012***	0.005**	-0.010	-0.012***	0.004**	-0.016*	-0.011***	0.005*	-0.006
		(0.003)	(0.003)	(0.011)	(0.002)	(0.002)	(0.011)	(0.003)	(0.002)	(0.009)	(0.003)	(0.003)	(0.013)
Wage 26	Unconditional WR	0.076***	0.072***	0.073***	0.071***	0.074***	0.078***	0.075***	0.076***	0.086***	0.060***	0.073***	0.073***
		(0.015)	(0.011)	(0.012)	(0.014)	(0.011)	(0.012)	(0.014)	(0.009)	(0.011)	(0.014)	(0.013)	(0.014)
	AM-AM	0.095***	0.047***	0.110***	0.090***	0.050***	0.121***	0.093***	0.057***	0.109***	0.078***	0.046***	0.129***
		(0.017)	(0.014)	(0.015)	(0.016)	(0.013)	(0.016)	(0.016)	(0.011)	(0.015)	(0.016)	(0.016)	(0.018)
	Diff	-0.020***	0.025***	-0.037***	-0.019**	0.024***	-0.043***	-0.019**	0.019***	-0.024**	-0.018**	0.027***	-0.056***
		(0.007)	(0.008)	(0.012)	(0.008)	(0.008)	(0.012)	(0.008)	(0.007)	(0.010)	(0.009)	(0.009)	(0.015)
	Change in match quality	-0.022***	0.025***	-0.037***	-0.019***	0.023***	-0.043***	-0.020***	0.019***	-0.024**	-0.017**	0.025***	-0.055***
		(0.007)	(0.008)	(0.012)	(0.007)	(0.008)	(0.013)	(0.007)	(0.007)	(0.011)	(0.008)	(0.008)	(0.015)
	Change in overeducation penalty	-0.005	0.023**	-0.014**	-0.005	0.021**	-0.017**	-0.005	0.015*	-0.009	-0.005	0.025**	-0.022***
		(0.006)	(0.010)	(0.007)	(0.006)	(0.009)	(0.008)	(0.006)	(0.008)	(0.007)	(0.006)	(0.010)	(0.008)
	Change in overeducation risk	-0.017***	0.001	-0.023***	-0.014***	0.002	-0.026***	-0.015***	0.005***	-0.015***	-0.012***	-0.000	-0.033***
		(0.003)	(0.002)	(0.006)	(0.003)	(0.002)	(0.006)	(0.003)	(0.002)	(0.005)	(0.003)	(0.002)	(0.008)
Wage 29	Unconditional WR	0.036**	0.090***	0.106***	0.040***	0.091***	0.111***	0.039***	0.086***	0.127***	0.047***	0.093***	0.101***
		(0.015)	(0.011)	(0.011)	(0.013)	(0.010)	(0.011)	(0.013)	(0.009)	(0.011)	(0.013)	(0.012)	(0.013)
	AM-AM	0.063***	0.067***	0.150***	0.068***	0.069***	0.162***	0.066***	0.073***	0.158***	0.075***	0.067***	0.165***
		(0.016)	(0.014)	(0.016)	(0.015)	(0.013)	(0.016)	(0.015)	(0.011)	(0.015)	(0.015)	(0.016)	(0.019)
	Diff	-0.027***	0.023***	-0.044***	-0.028***	0.021***	-0.051***	-0.027***	0.014**	-0.031***	-0.029***	0.026***	-0.065***
		(0.007)	(0.008)	(0.013)	(0.007)	(0.007)	(0.012)	(0.007)	(0.007)	(0.010)	(0.008)	(0.008)	(0.015)
	Change in match quality	-0.028***	0.023***	-0.044***	-0.027***	0.021***	-0.051***	-0.027***	0.015**	-0.032***	-0.026***	0.025***	-0.064***
		(0.007)	(0.008)	(0.013)	(0.007)	(0.007)	(0.013)	(0.007)	(0.007)	(0.010)	(0.007)	(0.008)	(0.015)
	Change in overeducation penalty	-0.013**	0.023**	-0.018**	-0.013**	0.020**	-0.023***	-0.013**	0.011	-0.016**	-0.013**	0.026***	-0.028***
		(0.006)	(0.009)	(0.007)	(0.006)	(0.009)	(0.008)	(0.006)	(0.008)	(0.007)	(0.006)	(0.010)	(0.009)
	Change in overeducation risk	-0.014***	0.000	-0.026***	-0.013***	0.001	-0.028***	-0.014***	0.004**	-0.015***	-0.013***	-0.001	-0.036***
		(0.003)	(0.002)	(0.006)	(0.003)	(0.002)	(0.006)	(0.003)	(0.002)	(0.005)	(0.003)	(0.002)	(0.008)

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).

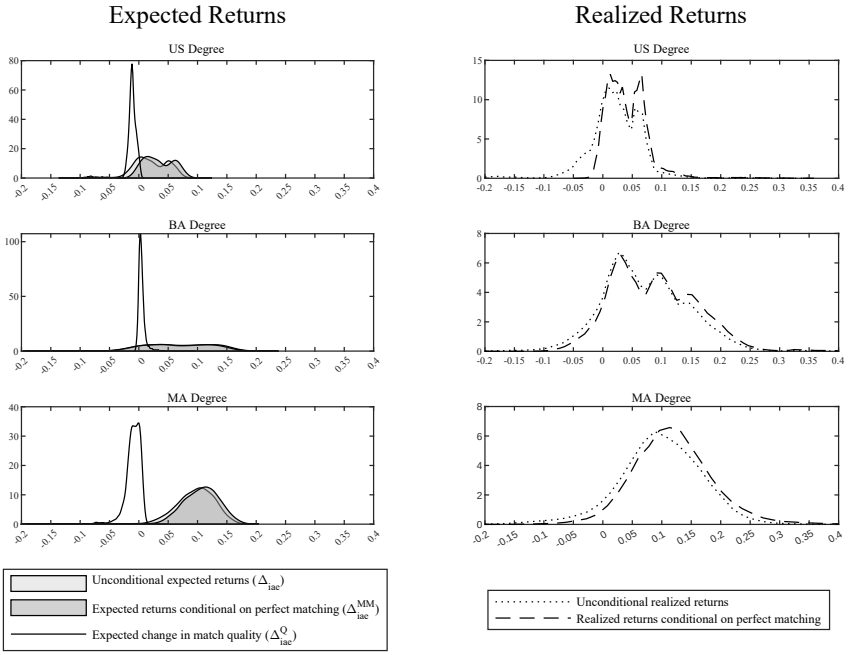
Table C11: Decomposition wage returns (Total)

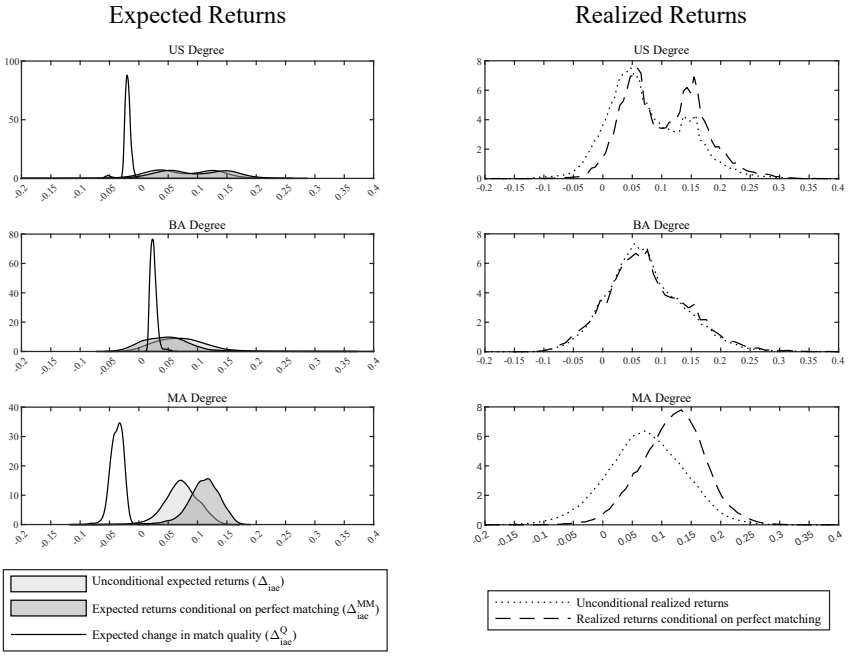
		Total effects											
		ATE†			ATE			ATT			ATNT		
		US	BA	MA	US	BA	MA	US	BA	MA	US	BA	MA
Wage 23	Unconditional WR	0.088***	0.088***	0.114***	0.064***	0.082***	0.099***	0.067***	0.088***	0.077***	0.045***	0.078***	0.113***
		(0.011)	(0.009)	(0.022)	(0.010)	(0.009)	(0.018)	(0.010)	(0.009)	(0.016)	(0.009)	(0.009)	(0.023)
	AM-AM	0.103***	0.087***	0.110***	0.080***	0.079***	0.101***	0.083***	0.086***	0.093***	0.062***	0.075***	0.106***
		(0.012)	(0.012)	(0.033)	(0.011)	(0.012)	(0.028)	(0.011)	(0.012)	(0.024)	(0.011)	(0.012)	(0.035)
	Difference	-0.016***	0.002	0.003	-0.016***	0.003	-0.002	-0.016***	0.002	-0.016	-0.016***	0.003	0.007
		(0.005)	(0.008)	(0.025)	(0.005)	(0.008)	(0.022)	(0.005)	(0.008)	(0.018)	(0.006)	(0.008)	(0.030)
	Change in match quality	-0.016***	0.002	0.010	-0.016***	0.002	0.005	-0.016***	0.002	-0.007	-0.016***	0.002	0.013
		(0.005)	(0.008)	(0.026)	(0.005)	(0.008)	(0.023)	(0.005)	(0.008)	(0.019)	(0.005)	(0.008)	(0.030)
	Change in overeducation penalty	-0.001	0.002	0.013	-0.002	0.002	0.010	-0.002	0.002	0.003	-0.002	0.002	0.015
		(0.003)	(0.008)	(0.019)	(0.003)	(0.008)	(0.017)	(0.003)	(0.008)	(0.014)	(0.003)	(0.008)	(0.021)
	Change in overeducation risk	-0.015***	0.000	-0.004	-0.015***	0.000	-0.005	-0.015***	0.000	-0.010*	-0.014***	0.000	-0.002
		(0.003)	(0.000)	(0.008)	(0.003)	(0.000)	(0.007)	(0.003)	(0.000)	(0.006)	(0.003)	(0.000)	(0.009)
Wage 26	Unconditional WR	0.132***	0.088***	0.095***	0.109***	0.080***	0.088***	0.113***	0.082***	0.084***	0.088***	0.079***	0.091***
		(0.013)	(0.008)	(0.014)	(0.012)	(0.008)	(0.012)	(0.012)	(0.008)	(0.011)	(0.011)	(0.009)	(0.015)
	AM-AM	0.142***	0.067***	0.133***	0.117***	0.058***	0.125***	0.121***	0.061***	0.106***	0.097***	0.056***	0.138***
		(0.014)	(0.010)	(0.019)	(0.013)	(0.011)	(0.017)	(0.013)	(0.011)	(0.015)	(0.012)	(0.011)	(0.020)
	Diff	-0.010**	0.020***	-0.038**	-0.008	0.022***	-0.037***	-0.008	0.021***	-0.022**	-0.009	0.023***	-0.047***
		(0.005)	(0.007)	(0.015)	(0.005)	(0.007)	(0.013)	(0.005)	(0.007)	(0.010)	(0.006)	(0.007)	(0.018)
	Change in match quality	-0.011**	0.021***	-0.037**	-0.009*	0.022***	-0.034**	-0.009*	0.022***	-0.021*	-0.008	0.022***	-0.043**
		(0.005)	(0.007)	(0.016)	(0.005)	(0.007)	(0.014)	(0.005)	(0.007)	(0.011)	(0.005)	(0.007)	(0.018)
	Change in overeducation penalty	0.001	0.021***	-0.025**	0.001	0.022***	-0.020*	0.001	0.022***	-0.011	0.001	0.022***	-0.027**
		(0.003)	(0.007)	(0.012)	(0.003)	(0.007)	(0.011)	(0.003)	(0.007)	(0.009)	(0.003)	(0.007)	(0.013)
	Change in overeducation risk	-0.012***	0.000	-0.012***	-0.010***	0.000	-0.014***	-0.010***	0.000	-0.010***	-0.009***	0.000	-0.017***
		(0.003)	(0.000)	(0.004)	(0.003)	(0.000)	(0.004)	(0.003)	(0.000)	(0.003)	(0.003)	(0.000)	(0.006)
Wage 29	Unconditional WR	0.094***	0.110***	0.108***	0.073***	0.099***	0.109***	0.075***	0.104***	0.122***	0.064***	0.096***	0.100***
		(0.013)	(0.008)	(0.014)	(0.011)	(0.008)	(0.012)	(0.011)	(0.008)	(0.011)	(0.011)	(0.008)	(0.014)
	AM-AM	0.112***	0.106***	0.167***	0.092***	0.095***	0.167***	0.093***	0.102***	0.156***	0.084***	0.091***	0.175***
		(0.014)	(0.011)	(0.020)	(0.013)	(0.011)	(0.017)	(0.013)	(0.011)	(0.015)	(0.012)	(0.011)	(0.021)
	Diff	-0.018***	0.004	-0.060***	-0.019***	0.004	-0.058***	-0.019***	0.002	-0.034***	-0.020***	0.005	-0.074***
		(0.005)	(0.007)	(0.015)	(0.005)	(0.007)	(0.013)	(0.005)	(0.007)	(0.010)	(0.006)	(0.007)	(0.018)
	Change in match quality	-0.018***	0.005	-0.059***	-0.018***	0.004	-0.055***	-0.018***	0.004	-0.034***	-0.019***	0.004	-0.069***
		(0.005)	(0.007)	(0.015)	(0.005)	(0.007)	(0.014)	(0.005)	(0.007)	(0.011)	(0.005)	(0.007)	(0.018)
	Change in overeducation penalty	-0.003	0.005	-0.040***	-0.003	0.004	-0.035***	-0.003	0.004	-0.024**	-0.004	0.004	-0.043***
		(0.003)	(0.007)	(0.012)	(0.003)	(0.007)	(0.011)	(0.003)	(0.007)	(0.009)	(0.003)	(0.007)	(0.013)
	Change in overeducation risk	-0.015***	0.000	-0.019***	-0.015***	0.000	-0.020***	-0.015***	0.000	-0.011***	-0.015***	0.000	-0.027***
		(0.003)	(0.000)	(0.005)	(0.003)	(0.000)	(0.004)	(0.003)	(0.000)	(0.003)	(0.003)	(0.000)	(0.006)

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).

C.1 Decomposition of Change in Match Quality Graphs

Figure C3: Decomposition of change in match quality (age 23 and 26)





D Model Estimates

Table D12: Model Estimates

			BM - K3	
			S.E.	p
Delay Primary Education	Female	0.004	0.181	0.984
	Siblings	1.551	0.268	0.000
	Foreign	0.059	0.051	0.249
	Education Father	0.011	0.031	0.717
	Education Mother	-0.009	0.034	0.800
	Birth day / 100	0.441	0.094	0.000
	Cohort 1978	0.046	0.308	0.882
	Cohort 1980	0.354	0.288	0.219
	Unemployment Rate	0.022	0.032	0.484
	Cons.	-5.837	0.536	0.000
	Het par 1	0.437	0.424	0.303
	Het par 2	0.070	0.297	0.815
Delay Secondary Education	Female	-0.270	0.079	0.001
	Siblings	0.809	0.135	0.000
	Foreign	0.096	0.025	0.000
	Education Father	-0.071	0.014	0.000
	Education Mother	-0.112	0.015	0.000
	Birth day / 100	0.297	0.040	0.000
	Cohort 1978	0.030	0.132	0.819
	Cohort 1980	-0.005	0.127	0.967
	Unemployment Rate	0.000	0.020	0.993
	Delay Primary Education	3.090	0.215	0.000
	Cons.	-1.924	0.269	0.000
	Het par 1	-0.453	0.226	0.046
	Het par 2	-0.470	0.132	0.000
Start and Track in LS	Female	0.410	0.049	0.000
	Siblings	0.180	0.125	0.151

Table D12 continued from previous page

	Foreign	-0.089	0.019	0.000
	Education Father	0.146	0.008	0.000
	Education Mother	0.125	0.009	0.000
	Birth day / 100	-0.076	0.025	0.002
	Cohort 1978	0.034	0.080	0.669
	Cohort 1980	-0.070	0.088	0.427
	Unemployment Rate	-0.026	0.011	0.021
	Delay Primary Education	0.916	0.224	0.000
	Delay Secondary Education	-1.977	0.109	0.000
	Het par 1	0.314	0.127	0.014
	Het par 2	0.368	0.077	0.000
	_cut_1	-4.354	0.181	0.000
	_cut_2	1.095	0.130	0.000
LS Degree	Female	0.664	0.130	0.000
	Siblings	-0.016	0.211	0.938
	Foreign	-0.118	0.034	0.001
	Education Father	0.118	0.025	0.000
	Education Mother	0.066	0.025	0.010
	Birth day / 100	0.006	0.062	0.923
	Cohort 1978	0.433	0.206	0.035
	Cohort 1980	0.383	0.197	0.052
	Unemployment Rate	-0.038	0.028	0.184
	Delay Primary Education	-0.455	0.338	0.179
	Delay Secondary Education	-0.718	0.144	0.000
	Track LS	1.923	0.219	0.000
	Cons.	2.007	0.328	0.000
	Het par 1	0.296	0.326	0.364
	Het par 2	0.496	0.204	0.015
Start and Track in US	Female	0.343	0.076	0.000
	Siblings	-0.065	0.185	0.725
	Foreign	-0.040	0.029	0.169
	Education Father	0.066	0.013	0.000
	Education Mother	0.068	0.014	0.000

Table D12 continued from previous page

	Birth day / 100	0.019	0.038	0.628
	Cohort 1978	0.389	0.111	0.000
	Cohort 1980	0.265	0.109	0.016
	Unemployment Rate	-0.057	0.018	0.001
	Delay Primary Education	-0.383	0.284	0.178
	Delay Secondary Education	-0.593	0.156	0.000
	Track LS	6.117	0.181	0.000
	Het par 1	0.161	0.185	0.385
	Het par 2	0.298	0.114	0.009
	_cut_1	-3.068	0.249	0.000
	_cut_2	5.103	0.291	0.000
US Degree	Female	0.671	0.110	0.000
	Siblings	-0.573	0.189	0.002
	Foreign	-0.080	0.033	0.016
	Education Father	0.065	0.020	0.001
	Education Mother	0.043	0.020	0.035
	Birth day / 100	0.119	0.053	0.023
	Cohort 1978	-0.195	0.160	0.225
	Cohort 1980	-0.197	0.158	0.211
	Unemployment Rate	-0.033	0.024	0.172
	Delay Primary Education	-0.277	0.339	0.414
	Delay Secondary Education	-0.621	0.138	0.000
	Track LS	0.165	0.176	0.350
	Track US	1.361	0.216	0.000
	Cons.	2.192	0.325	0.000
	Het par 1	-0.516	0.237	0.029
	Het par 2	-0.051	0.169	0.763
Start and Track in BA	Female	0.134	0.048	0.006
	Siblings	-0.100	0.139	0.470
	Foreign	-0.034	0.020	0.096
	Education Father	0.089	0.008	0.000
	Education Mother	0.059	0.009	0.000
	Birth day / 100	0.022	0.024	0.360

Table D12 continued from previous page

	Cohort 1978	0.244	0.071	0.001
	Cohort 1980	0.253	0.072	0.000
	Unemployment Rate	-0.011	0.011	0.318
	Delay Primary Education	0.359	0.230	0.118
	Delay Secondary Education	-0.715	0.104	0.000
	Track LS	1.241	0.094	0.000
	Track US	2.214	0.104	0.000
	Het par 1	0.136	0.124	0.273
	Het par 2	0.217	0.075	0.004
	_cut_1	1.112	0.157	0.000
	_cut_2	4.851	0.174	0.000
BA Degree and Grade	Female	0.422	0.053	0.000
	Siblings	-0.599	0.178	0.001
	Foreign	-0.043	0.023	0.064
	Education Father	0.010	0.009	0.264
	Education Mother	0.014	0.009	0.132
	Birth day / 100	-0.018	0.027	0.511
	Cohort 1978	-0.139	0.080	0.081
	Cohort 1980	-0.588	0.087	0.000
	Unemployment Rate	-0.235	0.012	0.000
	Delay Primary Education	0.131	0.270	0.627
	Delay Secondary Education	-0.536	0.149	0.000
	Track LS	0.039	0.103	0.709
	Track US	0.884	0.098	0.000
	Track BA	0.278	0.062	0.000
	Het par 1	0.023	0.135	0.864
	Het par 2	0.219	0.081	0.007
	_cut_1	-2.728	0.183	0.000
	_cut_2	-0.549	0.179	0.002
	_cut_3	1.700	0.186	0.000
Start and Track in MA	Female	-0.448	0.082	0.000
	Siblings	0.173	0.314	0.582
	Foreign	-0.012	0.039	0.765

Table D12 continued from previous page

	Education Father	0.045	0.013	0.001
	Education Mother	0.043	0.014	0.003
	Birth day / 100	0.030	0.041	0.475
	Cohort 1978	0.013	0.120	0.914
	Cohort 1980	-0.283	0.125	0.023
	Unemployment Rate	-0.403	0.019	0.000
	Delay Primary Education	0.832	0.475	0.080
	Delay Secondary Education	-0.410	0.301	0.173
	Track LS	-0.113	0.219	0.605
	Track US	0.976	0.196	0.000
	Track BA	3.004	0.094	0.000
	BA Grade Intermediate	-0.229	0.087	0.009
	BA Grade Excellent	-0.038	0.161	0.815
	Het par 1	1.242	0.192	0.000
	Het par 2	0.130	0.122	0.285
	_cut_1	-1.721	0.269	0.000
	_cut_2	-0.417	0.268	0.119
MA Degree and Grade	Female	0.147	0.093	0.116
	Siblings	-0.497	0.349	0.155
	Foreign	-0.042	0.044	0.339
	Education Father	-0.012	0.015	0.422
	Education Mother	0.003	0.016	0.830
	Birth day / 100	0.094	0.047	0.043
	Cohort 1978	-0.285	0.141	0.044
	Cohort 1980	-0.282	0.146	0.053
	Unemployment Rate	-0.171	0.022	0.000
	Delay Primary Education	0.528	0.485	0.276
	Delay Secondary Education	-0.914	0.383	0.017
	Track LS	-0.425	0.335	0.204
	Track US	0.234	0.296	0.428
	Track BA	0.218	0.168	0.194
	BA Grade Intermediate	1.723	0.111	0.000
	BA Grade Excellent	3.166	0.204	0.000

Table D12 continued from previous page

	Track MA	0.053	0.166	0.752
	Het par 1	-0.256	0.195	0.190
	Het par 2	0.125	0.141	0.374
	_cut_1	-3.451	0.344	0.000
	_cut_2	-1.233	0.332	0.000
	_cut_3	1.411	0.339	0.000
Overeducation	Female	0.631	0.232	0.007
	Siblings	0.007	0.136	0.958
	Foreign	0.150	0.059	0.012
	Education Father	-0.076	0.045	0.092
	Education Mother	0.036	0.043	0.401
	Birth day / 100	-0.018	0.113	0.875
	Cohort 1978	-0.210	0.081	0.010
	Cohort 1980	-0.100	0.084	0.230
	Unemployment Rate	0.029	0.012	0.016
	Delay Secondary Education	0.100	0.094	0.286
	Track LS	-0.212	0.307	0.489
	Track US	-0.068	0.334	0.839
	US	2.183	0.363	0.000
	Track BA	0.163	0.349	0.640
	BA	-0.504	0.255	0.048
	BA Grade Intermediate	-0.183	0.290	0.528
	BA Grade Excellent	-0.721	0.594	0.225
	Track MA	-0.135	0.543	0.804
	MA	1.953	0.512	0.000
	MA Grade Intermediate	-0.822	0.513	0.109
	MA Grade Excellent	-0.643	0.710	0.365
	US*Female	-0.863	0.243	0.000
	* Siblings	-0.095	0.063	0.136
	* Education Father	0.045	0.047	0.336
	* Education Mother	-0.061	0.045	0.180
	*Birth day / 100	-0.055	0.118	0.641
	BA*Female	-0.046	0.152	0.761

Table D12 continued from previous page

* Siblings	-0.073	0.063	0.246
* Education Father	0.058	0.025	0.021
* Education Mother	-0.017	0.027	0.522
*Birth day / 100	0.007	0.074	0.930
MA*Female	0.278	0.301	0.356
* Siblings	-0.088	0.133	0.508
* Education Father	-0.053	0.048	0.273
* Education Mother	0.060	0.051	0.235
*Birth day / 100	0.080	0.148	0.591
Track LS*Female	-0.156	0.189	0.410
* Siblings	-0.048	0.071	0.502
* Education Father	-0.023	0.032	0.467
* Education Mother	0.042	0.033	0.205
*Birth day / 100	0.115	0.092	0.213
Track US*Female	0.261	0.204	0.202
* Siblings	0.092	0.081	0.255
* Education Father	-0.019	0.033	0.561
* Education Mother	-0.022	0.036	0.542
*Birth day / 100	-0.012	0.100	0.903
Track BA*Female	0.238	0.205	0.246
* Siblings	-0.095	0.074	0.198
* Education Father	-0.007	0.032	0.830
* Education Mother	0.000	0.036	0.991
*Birth day / 100	-0.064	0.108	0.555
Track MA*Female	-0.112	0.311	0.720
* Siblings	-0.100	0.138	0.471
* Education Father	0.049	0.049	0.316
* Education Mother	-0.056	0.053	0.285
*Birth day / 100	0.003	0.155	0.985
BA Grade Intermediate*Female	-0.140	0.341	0.682
* Siblings	0.195	0.176	0.268
* Education Father	0.004	0.058	0.941
* Education Mother	-0.032	0.059	0.590

Table D12 continued from previous page

	*Birth day / 100	0.150	0.175	0.391
	BA Grade Excellent*Female	-0.218	0.171	0.202
	* Siblings	0.069	0.076	0.367
	* Education Father	-0.026	0.028	0.343
	* Education Mother	0.024	0.030	0.427
	*Birth day / 100	-0.001	0.085	0.991
	MA Grade Intermediate*Female	0.291	0.396	0.462
	* Siblings	0.032	0.187	0.865
	* Education Father	-0.043	0.071	0.544
	* Education Mother	0.036	0.071	0.616
	*Birth day / 100	-0.036	0.195	0.852
	MA Grade Excellent*Female	0.031	0.282	0.913
	* Siblings	0.187	0.134	0.163
	* Education Father	-0.001	0.046	0.976
	* Education Mother	0.025	0.049	0.608
	*Birth day / 100	-0.054	0.144	0.706
	Cons.	-1.935	0.381	0.000
	Het par 1	0.666	0.140	0.000
	Het par 2	-0.362	0.086	0.000
Wage Selection 23 years old	Female	0.121	0.057	0.032
	Siblings	-0.642	0.130	0.000
	Foreign	-0.051	0.020	0.012
	Education Father	-0.032	0.009	0.001
	Education Mother	-0.039	0.010	0.000
	Birth day / 100	-0.046	0.028	0.102
	Cohort 1978	0.922	0.086	0.000
	Cohort 1980	1.215	0.088	0.000
	Unemployment Rate	-0.037	0.014	0.006
	Delay Secondary Education	-0.222	0.096	0.020
	Track LS	-0.373	0.097	0.000
	LS	-0.086	0.167	0.606
	Track US	0.197	0.104	0.058
	US	-0.036	0.117	0.762

Table D12 continued from previous page

	Track BA	-0.443	0.105	0.000
	BA	-0.693	0.081	0.000
	BA Grade Intermediate	0.213	0.087	0.014
	BA Grade Excellent	0.366	0.172	0.033
	Track MA	-0.186	0.161	0.246
	MA	-1.602	0.156	0.000
	MA Grade Intermediate	0.413	0.162	0.011
	MA Grade Excellent	0.454	0.226	0.045
	Overeducation	0.100	0.060	0.095
	Cons.	1.415	0.217	0.000
	Het par 1	0.221	0.140	0.116
	Het par 2	-0.397	0.086	0.000
Log-hourly wage at 23 years old	Female	-0.098	0.016	0.000
	Siblings	0.024	0.014	0.092
	Foreign	-0.003	0.004	0.547
	Education Father	0.003	0.003	0.294
	Education Mother	-0.006	0.003	0.035
	Birth day / 100	0.000	0.007	0.952
	Cohort 1978	0.023	0.010	0.019
	Cohort 1980	0.037	0.010	0.000
	Unemployment Rate	0.001	0.001	0.507
	Delay Secondary Education	-0.017	0.009	0.078
	Track LS	0.007	0.036	0.856
	LS	0.028	0.016	0.080
	Track US	-0.037	0.041	0.376
	US	-0.013	0.029	0.659
	Track BA	0.056	0.051	0.271
	BA	0.046	0.033	0.167
	BA Grade Intermediate	-0.006	0.040	0.886
	BA Grade Excellent	0.161	0.081	0.047
	Track MA	0.144	0.098	0.143
	MA	0.076	0.097	0.431
	MA Grade Intermediate	-0.207	0.104	0.046

Table D12 continued from previous page

MA Grade Excellent	-0.062	0.136	0.647
Overeducation	0.027	0.032	0.399
Overeducation*US	-0.011	0.027	0.693
Overeducation*BA	0.000	0.019	0.988
Overeducation*MA	-0.006	0.059	0.926
US*Female	0.009	0.019	0.651
* Siblings	0.002	0.005	0.659
* Education Father	-0.002	0.003	0.597
* Education Mother	0.008	0.003	0.017
*Birth day / 100	0.002	0.009	0.827
BA*Female	0.075	0.019	0.000
* Siblings	0.001	0.008	0.918
* Education Father	0.001	0.003	0.839
* Education Mother	-0.003	0.003	0.297
*Birth day / 100	-0.004	0.009	0.619
MA*Female	-0.012	0.053	0.818
* Siblings	0.041	0.027	0.139
* Education Father	-0.008	0.008	0.330
* Education Mother	-0.008	0.009	0.374
*Birth day / 100	0.016	0.029	0.579
Track LS*Female	0.040	0.021	0.056
* Siblings	-0.004	0.008	0.597
* Education Father	0.000	0.004	0.945
* Education Mother	-0.004	0.004	0.289
*Birth day / 100	-0.004	0.010	0.690
Track US*Female	-0.028	0.024	0.238
* Siblings	0.000	0.009	0.993
* Education Father	-0.001	0.004	0.800
* Education Mother	0.007	0.004	0.122
*Birth day / 100	0.011	0.012	0.322
Track BA*Female	0.036	0.029	0.210
* Siblings	-0.015	0.011	0.178
* Education Father	0.002	0.005	0.618

Table D12 continued from previous page

* Education Mother	-0.007	0.005	0.167
*Birth day / 100	-0.011	0.015	0.440
Track MA*Female	-0.018	0.055	0.747
* Siblings	-0.053	0.027	0.045
* Education Father	-0.002	0.008	0.796
* Education Mother	0.006	0.009	0.503
*Birth day / 100	-0.018	0.026	0.500
BA Grade Intermediate*Female	-0.102	0.046	0.028
* Siblings	-0.017	0.021	0.422
* Education Father	-0.005	0.007	0.502
* Education Mother	0.003	0.007	0.661
*Birth day / 100	-0.030	0.021	0.150
BA Grade Excellent*Female	-0.004	0.024	0.878
* Siblings	0.004	0.010	0.729
* Education Father	0.004	0.004	0.325
* Education Mother	-0.003	0.004	0.389
*Birth day / 100	0.003	0.011	0.800
MA Grade Intermediate*Female	0.000	0.081	1.000
* Siblings	0.032	0.036	0.370
* Education Father	0.005	0.014	0.718
* Education Mother	-0.001	0.014	0.930
*Birth day / 100	0.035	0.038	0.351
MA Grade Excellent*Female	0.019	0.055	0.727
* Siblings	0.007	0.029	0.818
* Education Father	0.008	0.008	0.338
* Education Mother	0.011	0.009	0.259
*Birth day / 100	0.036	0.029	0.213
Overeducation*Female	-0.040	0.013	0.002
* Siblings	-0.002	0.005	0.637
* Education Father	-0.003	0.002	0.233
* Education Mother	0.000	0.002	0.969
*Birth day / 100	-0.009	0.006	0.125
Overeducation*BA Grade Intermediate	0.101	0.047	0.033

Table D12 continued from previous page

	* BA Grade Excellent	0.023	0.022	0.311
	Overeducation*MA Grade Intermediate	-0.066	0.080	0.411
	* MA Grade Excellent	-0.018	0.062	0.772
	Overeducation*Track LS	0.016	0.022	0.465
	Overeducation*Track US	0.000	0.024	0.992
	Overeducation*Track BA	-0.028	0.028	0.330
	Overeducation*Track MA	0.039	0.056	0.484
	Cons.	1.930	0.029	0.000
	Het par 1	0.324	0.026	0.000
	Overeducation*Het par 1	-0.185	0.032	0.000
	Het par 2	0.002	0.013	0.895
	Overeducation*Het par 2	-0.040	0.018	0.026
	Sigma	0.186	0.002	0.000
Wage Selection 26 years old	Female	-0.223	0.073	0.002
	Siblings	-0.377	0.178	0.034
	Foreign	0.016	0.027	0.556
	Education Father	0.006	0.013	0.613
	Education Mother	-0.025	0.013	0.056
	Birth day / 100	-0.072	0.035	0.041
	Cohort 1978	3.498	0.088	0.000
	Unemployment Rate	-0.082	0.017	0.000
	Delay Secondary Education	-0.036	0.122	0.767
	Track LS	-0.078	0.132	0.558
	LS	-0.345	0.211	0.103
	Track US	-0.023	0.142	0.869
	US	0.512	0.147	0.000
	Track BA	0.055	0.142	0.698
	BA	0.470	0.109	0.000
	BA Grade Intermediate	-0.123	0.116	0.288
	BA Grade Excellent	-0.356	0.228	0.119
	Track MA	0.082	0.201	0.682
	MA	-0.126	0.189	0.504
	MA Grade Intermediate	0.324	0.187	0.084

Table D12 continued from previous page

	MA Grade Excellent	0.483	0.270	0.074
	Overeducation	-0.017	0.077	0.829
	Cons.	-2.048	0.251	0.000
	Het par 1	5.493	0.277	0.000
	Het par 2	4.828	0.116	0.000
Log-hourly wage at 26 years old	Female	-0.171	0.021	0.000
	Siblings	0.034	0.017	0.049
	Foreign	0.006	0.005	0.162
	Education Father	0.009	0.004	0.030
	Education Mother	-0.004	0.004	0.294
	Birth day / 100	-0.008	0.010	0.428
	Cohort 1978	0.058	0.010	0.000
	Unemployment Rate	-0.002	0.001	0.163
	Delay Secondary Education	-0.023	0.011	0.035
	Track LS	0.020	0.036	0.567
	LS	-0.009	0.021	0.644
	Track US	0.007	0.038	0.859
	US	0.077	0.033	0.021
	Track BA	-0.063	0.038	0.098
	BA	0.039	0.029	0.186
	BA Grade Intermediate	0.032	0.032	0.312
	BA Grade Excellent	0.012	0.066	0.860
	Track MA	0.077	0.058	0.190
	MA	0.127	0.055	0.021
	MA Grade Intermediate	-0.111	0.054	0.039
	MA Grade Excellent	0.003	0.080	0.970
	Overeducation	0.003	0.036	0.943
	Overeducation*US	-0.025	0.032	0.432
	Overeducation*BA	0.044	0.018	0.014
	Overeducation*MA	0.021	0.032	0.513
	US*Female	0.095	0.024	0.000
	* Siblings	-0.014	0.006	0.012
	* Education Father	-0.008	0.004	0.075

Table D12 continued from previous page

* Education Mother	0.007	0.005	0.125
*Birth day / 100	0.002	0.011	0.849
BA*Female	0.043	0.017	0.013
* Siblings	0.005	0.007	0.463
* Education Father	-0.006	0.003	0.044
* Education Mother	0.001	0.003	0.712
*Birth day / 100	0.000	0.009	0.961
MA*Female	-0.026	0.030	0.377
* Siblings	-0.020	0.014	0.152
* Education Father	0.000	0.005	0.927
* Education Mother	-0.006	0.005	0.276
*Birth day / 100	-0.001	0.015	0.932
Track LS*Female	0.032	0.021	0.137
* Siblings	-0.010	0.009	0.282
* Education Father	-0.004	0.004	0.279
* Education Mother	0.002	0.004	0.621
*Birth day / 100	0.002	0.010	0.846
Track US*Female	-0.027	0.023	0.242
* Siblings	0.001	0.010	0.917
* Education Father	0.010	0.004	0.008
* Education Mother	-0.006	0.004	0.130
*Birth day / 100	-0.005	0.011	0.679
Track BA*Female	0.035	0.022	0.110
* Siblings	0.002	0.007	0.755
* Education Father	-0.003	0.004	0.397
* Education Mother	0.005	0.004	0.193
*Birth day / 100	0.001	0.012	0.949
Track MA*Female	0.001	0.032	0.966
* Siblings	0.010	0.014	0.492
* Education Father	0.008	0.005	0.095
* Education Mother	-0.002	0.005	0.724
*Birth day / 100	-0.035	0.016	0.035
BA Grade Intermediate*Female	0.034	0.038	0.367

Table D12 continued from previous page

* Siblings	0.036	0.020	0.064
* Education Father	0.007	0.006	0.276
* Education Mother	-0.013	0.006	0.039
*Birth day / 100	-0.008	0.021	0.704
BA Grade Excellent*Female	-0.038	0.018	0.036
* Siblings	0.016	0.008	0.044
* Education Father	-0.001	0.003	0.758
* Education Mother	0.002	0.003	0.616
*Birth day / 100	0.001	0.009	0.934
MA Grade Intermediate*Female	-0.036	0.042	0.391
* Siblings	0.000	0.020	0.990
* Education Father	0.001	0.007	0.845
* Education Mother	-0.004	0.007	0.618
*Birth day / 100	0.029	0.021	0.174
MA Grade Excellent*Female	0.018	0.028	0.507
* Siblings	-0.005	0.014	0.738
* Education Father	-0.004	0.004	0.382
* Education Mother	0.009	0.005	0.072
*Birth day / 100	0.052	0.015	0.000
Overeducation*Female	-0.038	0.013	0.002
* Siblings	0.000	0.004	0.934
* Education Father	0.002	0.002	0.258
* Education Mother	-0.004	0.002	0.090
*Birth day / 100	0.001	0.006	0.925
Overeducation*BA Grade Intermediate	-0.021	0.038	0.584
* BA Grade Excellent	-0.037	0.018	0.040
Overeducation*MA Grade Intermediate	0.050	0.043	0.240
* MA Grade Excellent	0.028	0.031	0.366
Overeducation*Track LS	-0.001	0.022	0.963
Overeducation*Track US	-0.027	0.023	0.248
Overeducation*Track BA	0.049	0.022	0.028
Overeducation*Track MA	-0.109	0.034	0.001
Cons.	1.943	0.032	0.000

Table D12 continued from previous page

	Het par 1	0.449	0.017	0.000
	Overeducation*Het par 1	-0.077	0.021	0.000
	Het par 2	0.037	0.011	0.001
	Overeducation*Het par 2	-0.008	0.013	0.524
	Sigma	0.161	0.002	0.000
Wage Selection 29 years old	Female	-0.126	0.077	0.104
	Siblings	-0.283	0.167	0.091
	Foreign	0.023	0.028	0.403
	Education Father	0.018	0.013	0.161
	Education Mother	-0.020	0.014	0.152
	Birth day / 100	-0.114	0.037	0.002
	Cohort 1980	5.940	0.230	0.000
	Unemployment Rate	-0.068	0.020	0.001
	Delay Secondary Education	-0.013	0.126	0.916
	Track LS	-0.053	0.137	0.700
	LS	-0.101	0.203	0.619
	Track US	-0.055	0.149	0.711
	US	0.361	0.143	0.012
	Track BA	0.249	0.163	0.127
	BA	0.501	0.117	0.000
	BA Grade Intermediate	-0.032	0.131	0.804
	BA Grade Excellent	0.303	0.278	0.276
	Track MA	-0.204	0.247	0.408
	MA	0.584	0.230	0.011
	MA Grade Intermediate	-0.295	0.223	0.185
	MA Grade Excellent	-0.205	0.347	0.555
	Overeducation	0.105	0.082	0.198
	Cons.	-4.897	0.338	0.000
	Het par 1	5.303	0.255	0.000
	Het par 2	7.246	0.243	0.000
Log-hourly wage at 29 years old	Female	-0.106	0.020	0.000
	Siblings	0.047	0.015	0.001
	Foreign	-0.004	0.005	0.379

Table D12 continued from previous page

Education Father	0.002	0.004	0.560
Education Mother	0.005	0.004	0.172
Birth day / 100	0.029	0.009	0.001
Cohort 1980	0.497	0.016	0.000
Unemployment Rate	-0.001	0.002	0.613
Delay Secondary Education	-0.030	0.010	0.004
Track LS	0.055	0.035	0.116
LS	-0.050	0.020	0.012
Track US	-0.015	0.037	0.689
US	0.143	0.031	0.000
Track BA	0.002	0.038	0.953
BA	0.026	0.029	0.377
BA Grade Intermediate	-0.015	0.030	0.620
BA Grade Excellent	0.040	0.061	0.515
Track MA	0.024	0.057	0.669
MA	0.039	0.051	0.449
MA Grade Intermediate	0.059	0.052	0.257
MA Grade Excellent	0.075	0.078	0.332
Overeducation	0.055	0.034	0.113
Overeducation*US	-0.073	0.030	0.016
Overeducation*BA	0.013	0.017	0.434
Overeducation*MA	-0.006	0.031	0.859
US*Female	0.021	0.022	0.331
* Siblings	0.006	0.006	0.326
* Education Father	-0.004	0.004	0.370
* Education Mother	-0.003	0.004	0.514
*Birth day / 100	-0.037	0.010	0.000
BA*Female	0.048	0.017	0.004
* Siblings	0.010	0.007	0.129
* Education Father	-0.001	0.003	0.824
* Education Mother	0.000	0.003	0.938
*Birth day / 100	0.002	0.008	0.824
MA*Female	-0.017	0.029	0.558

Table D12 continued from previous page

* Siblings	0.014	0.011	0.210
* Education Father	0.007	0.005	0.144
* Education Mother	0.000	0.005	0.945
*Birth day / 100	-0.006	0.014	0.699
Track LS*Female	0.042	0.021	0.043
* Siblings	-0.020	0.007	0.006
* Education Father	0.004	0.003	0.261
* Education Mother	-0.007	0.004	0.056
*Birth day / 100	-0.001	0.010	0.901
Track US*Female	-0.035	0.022	0.109
* Siblings	0.011	0.009	0.219
* Education Father	-0.001	0.003	0.737
* Education Mother	0.003	0.004	0.496
*Birth day / 100	-0.005	0.011	0.643
Track BA*Female	0.023	0.021	0.282
* Siblings	0.004	0.008	0.639
* Education Father	-0.004	0.003	0.223
* Education Mother	-0.001	0.004	0.688
*Birth day / 100	-0.005	0.011	0.658
Track MA*Female	-0.007	0.031	0.829
* Siblings	-0.002	0.013	0.865
* Education Father	0.002	0.005	0.666
* Education Mother	0.008	0.005	0.141
*Birth day / 100	0.001	0.016	0.927
BA Grade Intermediate*Female	0.009	0.034	0.784
* Siblings	-0.009	0.017	0.596
* Education Father	0.004	0.006	0.447
* Education Mother	-0.006	0.006	0.277
*Birth day / 100	0.011	0.017	0.523
BA Grade Excellent*Female	-0.027	0.018	0.121
* Siblings	0.006	0.008	0.423
* Education Father	-0.005	0.003	0.086
* Education Mother	0.005	0.003	0.124

Table D12 continued from previous page

*Birth day / 100	0.021	0.009	0.014
MA Grade Intermediate*Female	0.023	0.042	0.588
* Siblings	-0.062	0.020	0.002
* Education Father	-0.002	0.007	0.772
* Education Mother	-0.002	0.007	0.789
*Birth day / 100	0.020	0.020	0.324
MA Grade Excellent*Female	-0.019	0.027	0.477
* Siblings	-0.032	0.012	0.007
* Education Father	-0.007	0.004	0.085
* Education Mother	0.006	0.005	0.226
*Birth day / 100	0.011	0.014	0.433
Overeducation*Female	-0.021	0.012	0.078
* Siblings	-0.008	0.004	0.071
* Education Father	0.001	0.002	0.507
* Education Mother	-0.003	0.002	0.109
*Birth day / 100	0.007	0.006	0.208
Overeducation*BA Grade Intermediate	-0.013	0.035	0.703
* BA Grade Excellent	-0.001	0.018	0.968
Overeducation*MA Grade Intermediate	0.082	0.044	0.062
* MA Grade Excellent	0.011	0.030	0.712
Overeducation*Track LS	-0.036	0.021	0.092
Overeducation*Track US	0.030	0.022	0.181
Overeducation*Track BA	0.064	0.021	0.002
Overeducation*Track MA	-0.096	0.033	0.004
Cons.	1.525	0.036	0.000
Het par 1	0.805	0.026	0.000
Overeducation*Het par 1	-0.087	0.026	0.001
Het par 2	0.479	0.017	0.000
Overeducation*Het par 2	-0.017	0.012	0.150
Sigma	0.151	0.002	0.000
P(k==1)	0.764		
P(k==2)	0.044		
P(k==3)	0.192		

Table D12 continued from previous page

Log-likelihood	**-37756.93273**

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