Determinants of the choice for professional teacher education programs: A multinomial multilevel approach

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In recent years, concerns have risen regarding the Flemish teacher labour market : there is a fear of a decreasing quality of inflowing students in teacher education programmes. In this paper we investigate the transition from secondary school to higher education in Flanders, more specifically to professional teacher education programms (i.e. Bacherlor in Education). We used merged administrative databases from the Flemish Department of Education in order to construct a longitudinal dataset, enabling to track individual students from secondary to higher education. We obtained data from the entire population of secondary school leavers in the academic year 2004-2005 (n=51.902). These data allow tracking individual students during their higher education career from the academic year 2005-2006 until 2011-2012. The data include individual demographic student characteristics, detailed individual enrolment information in secondary education and higher education and a number of secondary school characteristics. Since pupils are nested in schools and in municipalities multilevel estimation techniques were used to model the transition from secondary education to various potential higher education programmes. Both random intercepts and random slopes models were estimated. Our findings show that the odds of enrolment in teacher education programs are highly influenced by several individual, secondary school and regional characteristics. While the differences with academic bachelors have been found to be more pronounced when considering most of the determinants, the inflow in teacher education was also found to be substantially different from the inflow in other professional programs. However, not all variance that is detected at the level of secondary schools can be explained by secondary school characteristics.

Keywords: word; Transition from secondary to higher education, teacher education, multinomial logistic regression, multilevel.

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INTRODUCTION

To gain more in-depth knowledge in the inflow in professional teacher education programmes, we compare the profiles of students who make different decisions when making the transition from secondary to higher education. We assume the decision making process of students to be stepwise. We suppose the first educational choice a student is confronted with is the choice between an academic or a professional programme. Conditionally on choosing for a professional programme, we break the student's transition options down to four professional 'clusters'. This way, it is possible to compare the differences in profiles of students who make different educational choices and therefore gain more insight into the inflow in the different professional programmes, including teacher education.

This report fits in with the research on education transitions, which has been expanding since its beginning in the 1980s (Mare 1980). More precisely, this report can be framed into a more recent wave within this tradition of research on education transitions that found its origin in addressing a limitation of the Mare model (Breen and Jonsson 2000, Benito and Alegre 2012). The limitation that is addressed is the implicit assumption that transitions can be considered as yes/no-questions, without taking into account the possibility of parallel branches of study (Mare 1980, Breen and Jonsson 2000, Benito and Alegre 2012). As Breen and Jonsson (2000) and Lucas (2001) argue, considering different parallel branches of study is relevant when investigating education transitions, since opting for different parallel branches might be influenced by different determinants.

International literature has been examining the influence of a multitude of determinants on the choice of a certain transition option when considering the transition from secondary to higher education. Four main categories of determinants have been distinguished. First, individual characteristics e.g. gender, age, ability and nationality are found to significantly influence the choice of field of study (Ayalon and Yogev 2005, Benito and Alegre 2012). Second, the transition choice is found to be highly influenced by family background characteristics such as type of family, number of siblings, education of the parents and family income (Van de Werfhorst, De Graaf et al. 2001, Nguyen and Taylor 2003, Van de Werfhorst, Sullivan et al. 2003, Ayalon and Yogev 2005). Third, Nguyen and Taylor (2003) and Benito and Alegre (2012) found the impact of certain secondary school characteristics (e.g. percentage of students from families with a low educational level and school type) to have a significant impact on the transition choices after secondary education. However, research on the impact of secondary school characteristics on transition options has been scarce so far (Nguyen and Taylor 2003, Benito and Alegre 2012). The literature on the influence of the school context on a student's educational achievement is more expanded (Leckie 2009, Owens 2010, Rasbash, Leckie et al. 2010, Sykes and Musterd 2011). Finally, regional characteristics such as geographic location have been found to play a part in educational achievement and the transition from secondary to tertiary education. For example, higher unemployment levels in the region you live can make you choose for programmes that lead to higher job security (Nguyen and Taylor 2003, Ayalon and Yogev 2005, Kauppinen 2008). One of the strengths of this paper is that not only individual characteristics of the student will be considered. It is hypothesised that the social contexts wherein a student lives influence the educational transition choices she or he makes. We will therefore explicitly take the secondary school and residence context into account when considering the educational choices of a student.

The remainder of this report is structured as follows : section 2 describes the data and methodology that were used for the analyses. Section 3 reports on the results of the different analyses. The final section presents concluding comments as well as implications for policy makers and indicates directions for further research.

DATA AND METHODOLOGY

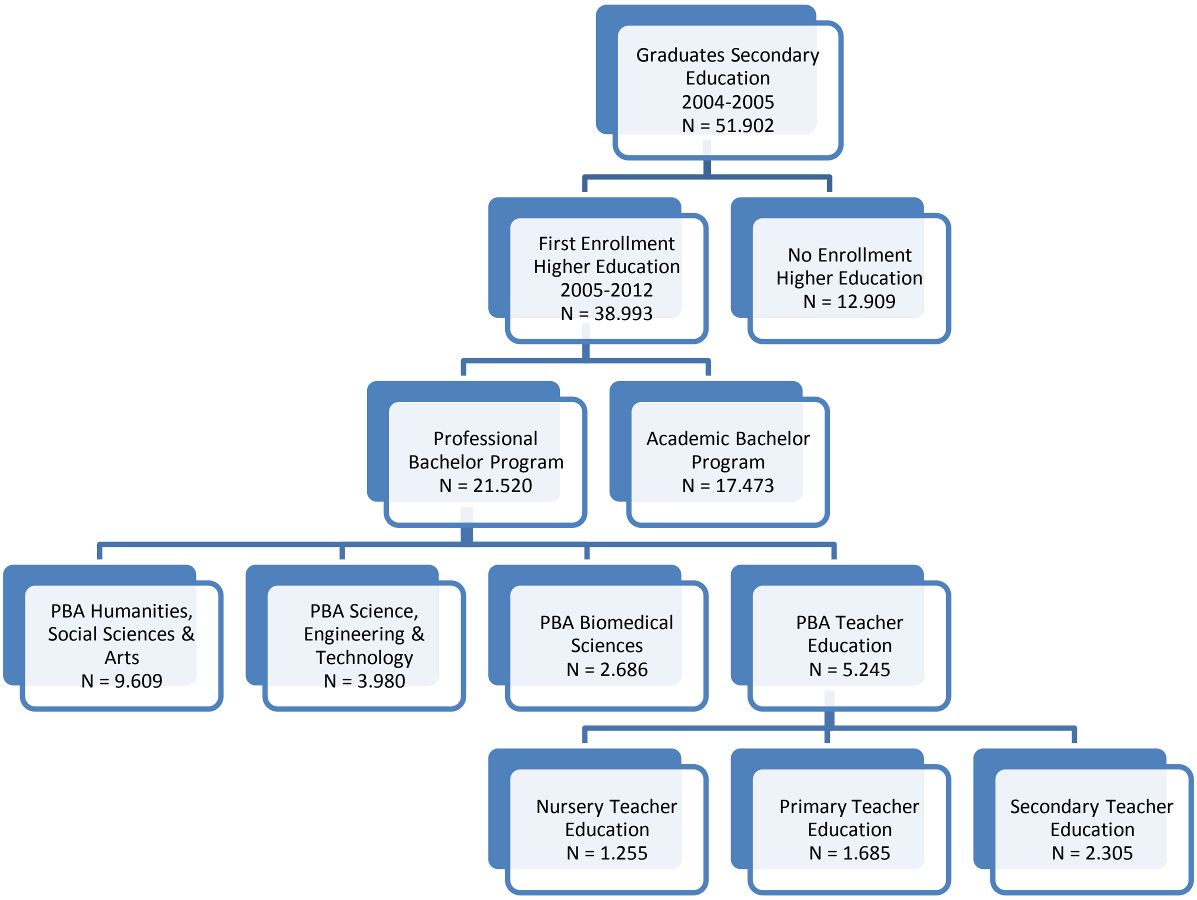
In this report we compare the profiles of students who enrol in different higher education programmes. We mainly focus on the inflow in different professional bachelor programme clusters by considering the importance of individual, secondary school and municipality effects. In this chapter, the data and methodology to make these comparisons possible are clarified.

Data

The data used in this report are subsets of newly linked administrative data provided by the Flemish Department of Education. These data enabled us to consider the transition from secondary to higher education of a population cohort of students who graduated from secondary education in the academic year 2004-2005. This dataset includes information on both student characteristics (e.g. gender, nationality, year of birth, grade retention), detailed individual enrolment information in secondary and higher education, as well as a number of school and regional characteristics.

Data on 51.902 pupils who graduated from secondary education in 2004-2005 were linked to higher education data from the period 2005-2012. Based on the time of registration, the first enrollment in higher education was selected for every student. 38.993 of the 51.902 graduates enrolled in higher education during the considered period 2005-2012. Subsequently, those students who enrolled in a professional bachelor programme were selected. Next, these professional bachelor programmes were subdivided into 4 major clusters of field of study: PBA Teacher Education, PBA Humanities, Social Sciences & Arts, PBA Biomedical Sciences and PBA Technology, Engineering & Science. Finally, the professional programme of teacher education can divided into three major categories: nursery, primary and secondary teacher education programmes. These subdivisions and the number of students are represented in Figure 1.

Figure 5: Data selection



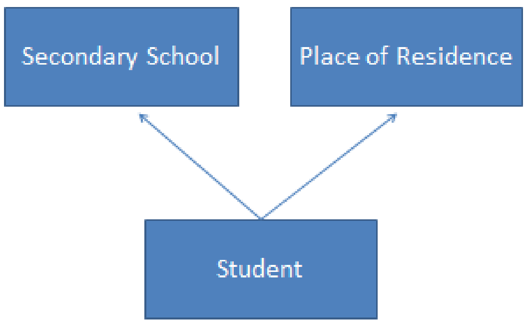
While these administrative data can be considered as a rich source of information for research, there is a major drawback that should be mentioned. As mentioned in the introduction of this report, educational choices are highly influenced by family background characteristics such as type of family, number of siblings, education of the parents and family income (Van de Werfhorst, De Graaf et al. 2001, Nguyen and Taylor 2003, Van de Werfhorst, Sullivan et al. 2003, Ayalon and Yogev 2005). However, no such information is available in the provided administrative databases. It should therefore be noted that attention should be paid when interpreting the results of the analyses, as they might be influenced by omitted variable bias: Because family background characteristics are likely to be correlated with variables such as nationality, educational choice and even the school you go to and the municipality you live in. The estimated effects might therefore be influenced by the omission of these family background characteristics.

Research Design and Methodology

Multinomial logistic multilevel models were used to compare the differences in profiles of students who make different educational transition choices. Preliminary single level multinomial models where seven fields of study (three academic and four professional fields of study) were compared indicated that major differences existed between academic and professional programmes, rather than between the different fields of study. It was therefore decided to conduct the multilevel analyses in two steps, where each time a different outcome variable or educational choices was/were considered, namely : (1) the transition to a professional or an academic bachelor programme and (2) the choice for one of the four professional bachelor programme clusters. The focus of this paper is on the second transition, i.e. conditional upon choosing a professional bachelor, rather than an academic bachelor. The aim of these analyses is to acquire more insight into the profiles of students who opt for a professional teacher education program in Flanders by comparing these students to students who opt for other higher education programmes. While doing this, we will not only consider differences in individual characteristics, but also consider the social contexts wherein students make their educational choices in. More precisely, we assume some variation in educational choices can be explained by taking into account the secondary school and the place of residence, as measured by the municipality a student lives in.

The structure of these data is non-hierarchical, since schools and residences are not necessarily nested: pupils are nested in schools and municipalities, but schools and municipalities are not necessarily nested within each other. It is however true that students often frequent secondary schools in the vicinity of their place of residence. This results in a high correlation between both social contexts. Therefore, it may be necessarily to take both schools and the place of residence into account in this kind of analyses, to be able to distinguish the effect of both contexts (See for example Owens (2010)). Figure 2 is a classification diagram, which represents the data structure in our models (Leckie 2009, Leckie 2013). As can be seen, pupils are nested in a cross-classification of their secondary schools and place of residence.

Figure 6: Classification diagram



This type of data structure is best modeled using cross-classified multilevel analysis (Leckie 2013). The estimation of multinomial multilevel and cross-classified models using traditional maximum likelihood techniques lead to important computational limitations and difficulties (Browne and Rasbash 2009, Leckie 2009). Therefore, MCMC (Markov Chain Monte Carlo) estimation procedures (Browne and Rasbash 2009) with a minimum of 5000 iterations are used. The analyses were conducted using the MLwiN programme version 2.28 (Rasbash, Browne et al. 2000) with starting values from computational simpler models using traditional maximum likelihood estimation techniques, namely iterative generalised least squares (Leckie 2009). This analysis strategy is based on Jen et al. (2009).

The model fit is assessed in two ways. First, the Bayesian deviance information criterion is used (Browne and Rasbash 2009, Jen, Jones et al. 2009, Leckie 2009). A smaller DIC-value indicates a better fit of the model, where a difference of 10 can be considered as substantial. Second, we considered figures of residuals and predicted probabilities to assess model fit and the importance of the school and municipal contexts.

For each educational transition choice, a set of models will be considered. When conducting multilevel analyses, it is common to start with estimating unconditional models, or so-called null models. This is useful to get an insight in whether a multilevel analysis structure is appropriate, and if so, which one should be applied. Four possible structures will be compared:

1) A single level model, which does not take into account that some variation in the educational choices might lie at the secondary school or the residence level;
2) an unconditional multilevel model where municipality is included as higher level;
3) an unconditional multilevel model with schools included as higher level;
4) and a cross-classified unconditional multilevel model where both the place of residence and schools are included as higher levels.

Subsequently, model fit assessment is used to determine the optimal multilevel structure. This structure is then used to conduct analyses where step by step the individual and school factors will be included. Two final remarks should be made in this section. First, coefficients are considered to be significant when their absolute value is more than twice the value of the respective standard error. Second, all continuous variables are grand mean centered in the analyses. This operation does not change the outcomes of the analyses, but facilitates computation.

Variables

Outcome variables

The dependent variables considered in this report are different subsets of postsecondary educational choices. As mentioned earlier, the aim of these analyses is to acquire an insight into the student population of professional teacher education programmes by comparing them to students who make other educational transition choices (more specifically other professional bachelor programmes) : students who enroll in professional programmes are selected and divided into four different professional programme clusters, which are then compared. These selections and the number of students in every educational transition option considered were depicted by Figure 5.

Level 1: Explanatory variables at the individual level

The variables considered at the individual level are gender, grade retention, nationality and education form. Men will be considered as the reference category of the gender variable for all analyses. The variable grade retention is in these analyses considered as a proxy for educational ability, since no prior educational achievement data was available. Other Flemish studies have used grade retention as an indicator for academic ability before, considering grade retention as an indicator of poor academic achievement (Alexander, Entwisle et al. 2002, Agirdag, Van Houtte et al. 2012). This variable is then coded as a dummy variable (0 = no grade retention, 1 = at least one year of grade retention). No grade retention is considered as the reference category in the analyses. Finally, the nationality variable is a binary variable (0 = Belgian; 1 = non-Belgian) and is constructed based on the nationality of the student as mentioned on his or her identity card or other documents of identification when the student registered for secondary school. The final variable that will be considered is the education form the student attended in his last year of secondary education. Four different education forms can be distinguished when considering the third stage (i.e. the last two or three years) of Flemish mainstream secondary education (definitions below are taken from Department of Education and Training (2008)):

- General secondary education (ASO) places an emphasis on broad general education. This form of education provides a firm foundation for passing on to tertiary education. This education form is used as reference category in the analyses.
- Technical secondary education (TSO) places a special emphasis on general and technical/theoretical subjects. After this form of education, students can exercise a profession or pass on to tertiary education.
- Secondary arts education (KSO) combines a broad general education with active arts practice. After this form of education, students can exercise a profession or go on to tertiary education.
- Vocational secondary education (BSO) is a practice oriented type of education where students learn a specific occupation in addition to receiving general education. In Belgium, education is compulsory until the age of 18. However, from the age of 15 onwards, students following vocational secondary education can opt for part-time education.

Level 2: Explanatory variables at the school and residence level

The secondary school level is identified by a school ID code. A strength is that the school composition variables available in the databases of the Department of Education are no averages of the students in our analyses, but reflect the composition of the entire school. Five secondary school variables are considered. The first three variables are the percentages (range 0-100%) of students in the three major different educational forms (ASO, TSO, BSO). The fourth variable is the proportion of 'equal opportunities' students in the second and third degree compared to all students in these two degrees. An 'equal opportunities' student in the second or third degree is defined as a student who can be characterised by at least one of the following indicators:

- The student did repeat more than one year
- The student changed schools and attended technical or vocational secondary education after his or her previous class committee decided the pupil did not sufficiently achieve the objectives of the curriculum[1]

[1] For those familiar with the Flemish educational system: The student received a B - or C-certificate

- The student went to a reception class for foreign speaking newcomers in the previous academic year

Therefore, the proportion of 'equal opportunities' indicates the proportion of students with at least one of these characteristics. This variable can vary from zero to one. Finally, the fifth variable considered is the educational network a school belongs to. This is a categorical variable with three categories that are:

- GO! Education of the Flemish Community, which is publicly run education organised under the authority of the Flemish Community. The GO! is required to be neutral: All religious, philosophical and ideological convictions of parents and pupils have to be respected.
- Publicly funded, publicly run education (OGO), which comprises municipal education as well as provincial education.
- Publicly funded, privately run education (VGO), which delivers education organised by a private organisation. This educational network mainly consists of catholic schools. This category will be used as the reference category in the analyses.

Finally, we will consider the place of residence of the students as a potential level in our analyses. We were provided with a municipality ID-code, which allows us to consider effects on the level of municipalities.

RESULTS

We divided all Flemish professional bachelor (PBA) programmes into four major clusters : PBA Teacher Education (which will be used as the reference category throughout the analyses), PBA Humanities, Social Sciences & Arts, PBA Biomedical Sciences and PBA Science, Engineering and Technology. Multinomial multilevel analyses are used to compare these four clusters. We start by comparing some unconditional models to decide which multilevel structure leads to the best fit, after which models are estimated where variables at both the individual and school level are included.

Unconditional Models

In the following tables we compare a single level model (Table 7) with a multilevel model with as higher level municipalities (Table 8), a multilevel model with as higher level secondary schools (Table 9) and finally a cross-classified model with both municipalities and secondary schools as higher levels (Table 10). The unconditional models indicate that the variance at the residence level seems to be significant when secondary schools are not taken into account (Model 2), but when secondary schools and municipalities are taken into account simultaneously (Model 4), the variation at the residence level is greatly reduced. The DIC-values clearly indicate the hierarchical multilevel model where only secondary schools are included as the higher level is superior to the other models. In the next section, we will use this multilevel structure when including the variables at the individual and school level in our model.

Table 7: Unconditional models, comparison PBA clusters : single level

reference = PBA Teacher Education	SINGLE LEVEL		
	HUMANITIES	BIOMEDICAL	TECHNOLOGY
	Model 1a (S.E.)	Model 1b (S.E.)	Model 1c (S.E.)
Fixed parameters			
Constant	0.605(0.017)*	-0.670(0.023)*	-0.277(0.021)*
Deviance information criterion (DIC)	54923		
Number of students	21520		
Number of municipalities	-		
Number of schools	-		

* p<0.05

Table 8: Unconditional models, comparison PBA clusters : multilevel (place of residence)

reference = PBA Teacher Education	MULTILEVEL : LEVEL 2 = PLACE OF RESIDENCE		
	HUMANITIES	BIOMEDICAL	TECHNOLOGY
	Model 2a (S.E.)	Model 2b (S.E.)	Model 2c (S.E.)
Fixed parameters			
Constant	0.672(0.035)*	-0.727(0.041)*	-0.522(0.073)*
Random parameters			
Level 2 : residence			
Variance	0.235(0.034)*	0.219(0.039)*	1.357(0.157)*
covariance a & b°	0.027(0.027)		
covariance a & c°	0.084(0.055)		
covariance b & c°	-0.013(0.059)		
Deviance information criterion (DIC)	51922		
Number of students	21520		
Number of municipalities	362		
Number of schools	-		

°a = HUMANITIES; b = BIOMEDICAL; c = TECHNOLOGY   * p<0.05

Table 9: Unconditional models, comparison PBA clusters : multilevel (schools)

reference = PBA Teacher Education	MULTILEVEL : LEVEL 2 = SCHOOLS		
	HUMANITIES	BIOMEDICAL	TECHNOLOGY
	Model 3a (S.E.)	Model 3b (S.E.)	Model 3c (S.E.)
Fixed parameters			
Constant	0.570(0.032)*	-0.847(0.040)*	-0.696(0.068)*
Random parameters			
Level 2 : schools			
Variance	0.368(0.038)*	0.342(0.047)*	2.309(0.183)*
covariance a & b°	0.031(0.030)		
covariance a & c°	-0.062(0.063)		
covariance b & c°	-0.286(0.075)*		
Deviance information criterion (DIC)	48130		
Number of students	21520		
Number of municipalities	-		
Number of schools	665		

°a = HUMANITIES; b = BIOMEDICAL; c = TECHNOLOGY * $p<0.05$

Table 10: Unconditional models, comparison PBA clusters : multilevel (cross-classification)

reference = PBA Teacher Education	MULTILEVEL : LEVEL 2 = CROSS-CLASSIFICATION		
	HUMANITIES	BIOMEDICAL	TECHNOLOGY
	Model 4a (S.E.)	Model 4b (S.E.)	Model 4c (S.E.)
Fixed parameters			
Constant	0.679(0.052)*	-0.706(0.056)*	-1.048(0.120)*
Random parameters			
Level 2: residence			
Variance	0.035(0.016)*	0.015(0.010)	0.026(0.020)
covariance a & b°	0.005(0.011)		
covariance a & c°	-0.006(0.012)		
covariance b & c°	-0.001(0.009)		
Level 2 : schools			
Variance	0.382(0.042)*	0.346(0.049)*	2.681(0.243)*
covariance a & b°	0.057(0.035)		
covariance a & c°	-0.075(0.075)		
covariance b & c°	-0.295(0.088)*		
Deviance information criterion (DIC)	48300		
Number of students	21520		
Number of municipalities	362		
Number of schools	665		

Characteristics at the individual and school level

The results of the models wherein individual and school level variables are considered, are depicted in Table 11. Model 5 is a random intercept model where only the influence of individual factors is considered. In Model 6, the significant school level variables are included in the random intercept model. Model 7 is a random slopes model where the effects of the individual factors are allowed to vary across schools. The covariance structure of this model is considered to be diagonal. The percentage of students in technical and vocational secondary education, the proportion of equal opportunities students and the educational networks were not found to influence the probability of opting for a specific professional bachelor cluster. We did not report all the estimated models including these school factors, but chi-square tests to evaluate the significance of the included variables and the DIC-values to evaluate model fit indicated the model where only the percentage of general secondary education students was included at the school level was superior to models where other school factors were taken into account. The inclusion of random slopes in Model 7 leads to a major improvement of the model fit, as indicated by the decrease of the DIC-value.

Table 11: Individual and school level variables, comparison PBA clusters

reference = PBA Teacher Education	Random Intercept Model			Random Intercept Model			Random Slopes Model		
	HUMANITIES	BIOMEDICAL	TECHNOLOGY	HUMANITIES	BIOMEDICAL	TECHNOLOGY	HUMANITIES	BIOMEDICAL	TECHNOLOGY
	Model 5a (SE)	Model 5b (SE)	Model 5c (SE)	Model 6a (SE)	Model 6b (SE)	Model 6c (SE)	Model 7a (SE)	Model 7b (SE)	Model 7c (SE)
Fixed parameters									
Constant	1.077(0.054)*	-1.353(0.078)*	0.115(0.084)	1.036(0.06)*	-1.301(0.085)*	0.295(0.090)*	1.034(0.061)*	-1.247(0.087)*	0.185(0.089)*
Individual factors Educational form (ref. category = ASO)									
BSO	-0.677(0.078)*	-0.510(0.102)*	-0.533(0.126)*	-0.624(0.088)*	-0.588(0.117)*	-0.801(0.141)*	-0.613(0.108)*	-1.277(0.202)*	-0.796(0.194)*
TSO	-0.143(0.052)*	-0.079(0.065)	0.190(0.084)*	-0.096(0.064)	-0.156(0.085)	-0.063(0.101)	-0.086(0.081)	-0.255(0.097)*	0.038(0.134)
KSO	-0.818(0.164)*	-2.127(0.307)*	1.573(0.198)*	-0.755(0.173)*	-2.208(0.307)*	1.284(0.207)*	-0.627(0.175)*	-1.965(0.366)*	1.301(0.255)*
Female (ref. category = male)	-0.677(0.041)*	0.917(0.068)*	-1.862(0.060)*	-0.679(0.041)*	0.918(0.067)*	-1.860(0.059)*	-0.674(0.043)*	0.917(0.069)*	-1.877(0.068)*
grade_retention	0.097(0.041)*	-0.100(0.058)	0.067(0.056)	0.099(0.040)*	-0.100(0.058)	0.064(0.056)	0.095(0.042)*	-0.133(0.059)*	0.070(0.058)
Non-Belgian (ref. category = Belgian)	0.942(0.169)*	0.687(0.221)*	0.629(0.241)*	0.934(0.168)*	0.676(0.221)*	0.603(0.238)*	1.015(0.18)*	0.721(0.233)*	0.455(0.343)
Secondary school factors									
percentage_ASO				0.003(0.001)*	-0.002(0.001)	-0.011(0.002)*	0.003(0.001)*	-0.002(0.001)	-0.005(0.002)*
Random parameters school level									
Variance	0.383(0.040)*	0.273(0.040)*	1.401(0.125)*	0.383(0.039)*	0.266(0.039)*	1.286(0.166)*	See **Table 12**		
covariance a & b°	0.025(0.030)			0.029(0.029)					
covariance a & c°	-0.103(0.051)*			-0.087(0.05)					
covariance b & c°	0.056(0.060)			0.043(0.056)					
Deviance information criterion (DIC)	46219			46202			45689		
Number of students	21520			21520			21520		
Numer of schools	665			665			665		

°a = HUMANITIES; b = BIOMEDICAL; c = TECHNOLOGY * p<0.05

When considering the estimated random effects in Table 12, it becomes clear that the effect of the BSO and TSO-indicators are significantly different across secondary schools. This is true for all clusters. Apart from the constant, the other random effects are not found to be significant, indicating that the effect of these variables does not significantly vary across schools.

Table 12: Individual and school level variables, comparison PBA clusters, random effects model 7

	variance (S.E.)
cons_humanities	0.122(0.031)*
cons_biomedical	0.038(0.033)
cons_technology	0.240(0.087)*
BSO_humanities	0.471(0.184)*
TSO_humanities	0.587(0.087)*
KSO_humanities	0.078(0.128)
BSO_biomedical	1.675(0.439)*
TSO_biomedical	0.324(0.081)*
KSO_biomedical	0.337(0.639)
BSO_technology	1.574(0.555)*
TSO_techology	2.235(0.294)*
KSO_technology	0.763(0.616)
women_humanities	0.057(0.029)
women_biomedical	0.021(0.022)
women_technology	0.117(0.090)
grad_ret_humanities	0.009(0.011)
grad_ret_biomedical	0.012(0.017)
grad_ret_technology	0.027(0.034)
non-Belgian_humanities	0.223(0.356)
non-Belgian_biomedical	0.070(0.134)
non-Belgian_technology	0.970(1.223)

* $p<0.05$

So why are the effects of vocational and technical secondary education so different across schools? We believe this can be explained by the heterogeneity of technical and vocational secondary education. A wide range of specialisations and trainings are offered, and we assume the differences in effects can be explained by the different offer of specialisations and trainings in the secondary schools. This idea needs some additional explanation. When considering Table 13, it becomes clear that the inflow of a vocational student in a specific professional cluster in higher education depends on the specialialisation this student chose. While more than 60 different specialisations are offered in vocational secondary education, we can see that for every cluster more than 50 percent of the inflow of vocational students can be attributed to five specialisations. For the education, humanities and biomedical cluster, more than 75 percent of these students come from five specialisations. The effect of vocational (and technical) secondary education will therefore vary across schools, because not all secondary schools offer the same specialisations. We checked this for some schools where the vocational effect was estimated to be very high compared to the other schools when considering the technology cluster, and found that these schools mainly offered technical specialisations.

Table 13: Most frequented specialisations in vocational secondary education according to chosen professional cluster (% of vocational students inflowed in the according cluster)

Name of specialisation in vocational secondary education	Education	Humanities	Biomedical	Technology
Administration and Data Management	30.8%	61.1%	8.7%	15.7%
Child Care	28.9%	6.6%	21.0%	1.8%
Unnamed Year	6.3%	8.4%	1.3%	13.8%
Hair Stylist	5.5%	1.5%	0.4%	0.5%
Shop Management and Window Dressing	4.8%	3.4%	3.1%	3.2%
Domiciliary and Eldery Care	2.8%	2.1%	21.0%	1.8%
Nursing	0.4%	0.6%	36.2%	0.0%
Industrial Electricity	1.4%	1.2%	0.0%	8.8%
Publicity and Illustration	1.2%	1.2%	0.9%	7.4%
Green Management	0.5%	0.0%	0.0%	5.1%
Sum of 5 most frequent specialisations	76.2%	81.6%	87.3%	50.7%

Interpretation of the variables at the individual level

In this section we focus on the interpretation of the variables at the individual level based on the outcomes of Model 7 in Table 11. Considering the probabilities of education forms in Figure 7, we can see that vocational students have a higher probability than the other education forms to enroll in the Education cluster. The enrolment probabilities of vocational students (BSO) in the Education and Humanities clusters are not significantly different, while the latter is a much bigger cluster in which far more students enroll (see Figure 5 for the numbers of students enrolling in the different professional clusters). The enrolment probabilities of the other three education forms within the cluster of Education do not significantly differ from each other. The profiles of the other three clusters look quite similar to each other when considering the proportions of education forms. The only real noticable difference is the enrolment probabilities of the secondary arts students in the different clusters, particularly the technology cluster. This can be explained by the fact that subjects such as architecture and product development are included in this cluster.

Figure 7: Predicted probabilities of continuing to a specific professional cluster by education form

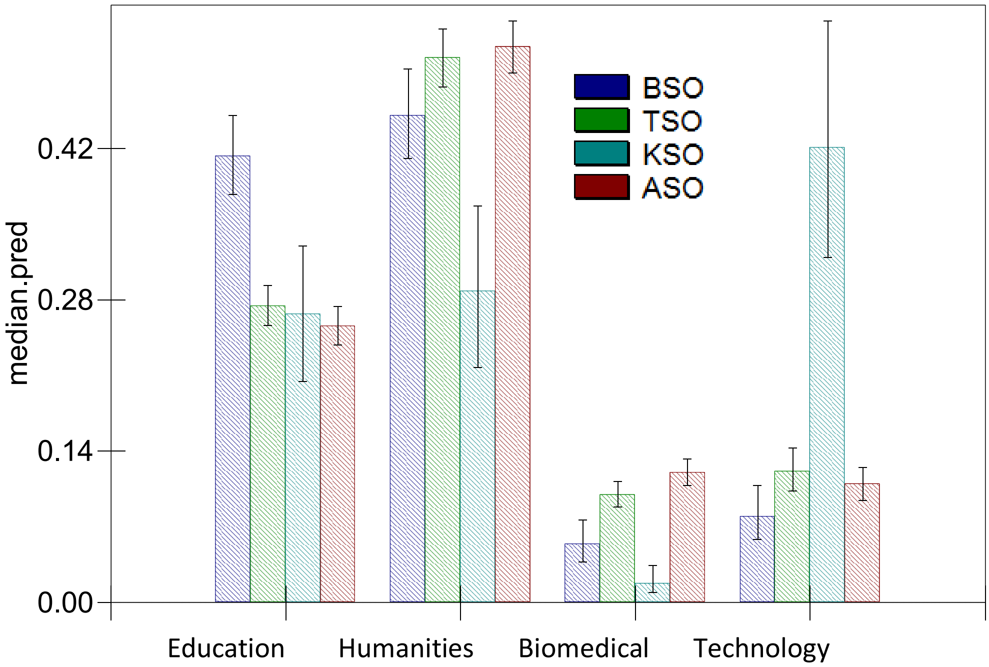
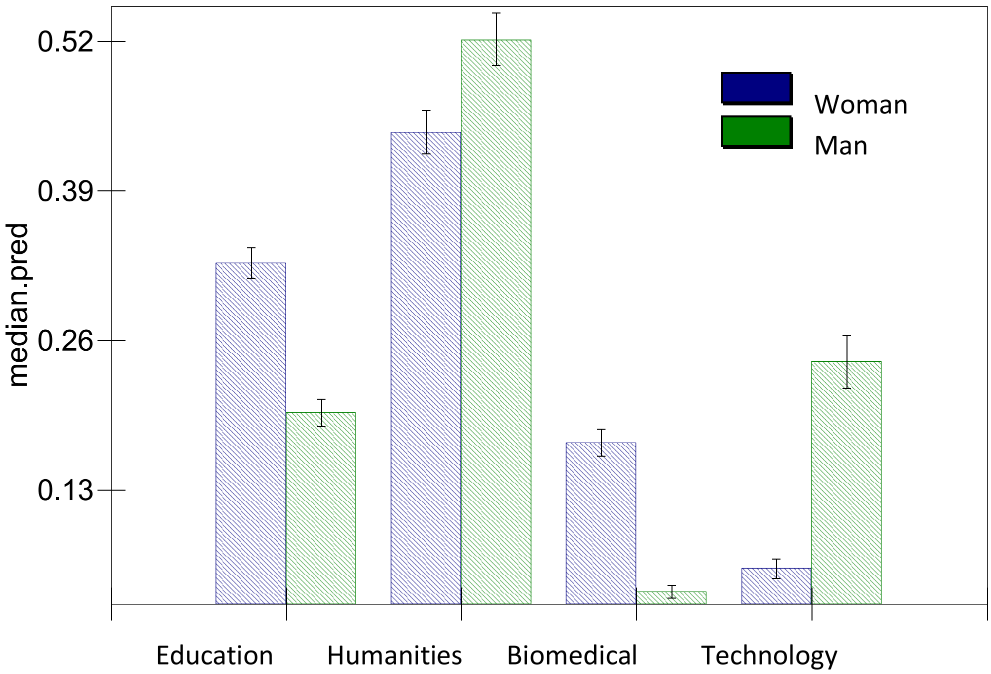


Figure 8 reports the transition probabilities to each cluster according to gender. The feminine character of the Education and Biomedical clusters is very clear: Women are more likely to opt for these clusters than men, ceteris paribus. The opposite is true for the Humanities and the Technology cluster. However, disparity between the transition probabilities of both sexes is much more clear-cut for the latter.

Figure 8: Predicted probabilities of continuing to a specific professional cluster by gender



Regarding grade retention we did not find significant differences between the enrolment probabilities for the four professional clusters when both types of students are compared. This can be seen in Figure 9.

Figure 9: Predicted probabilities of continuing to a specific professional cluster, grade retention

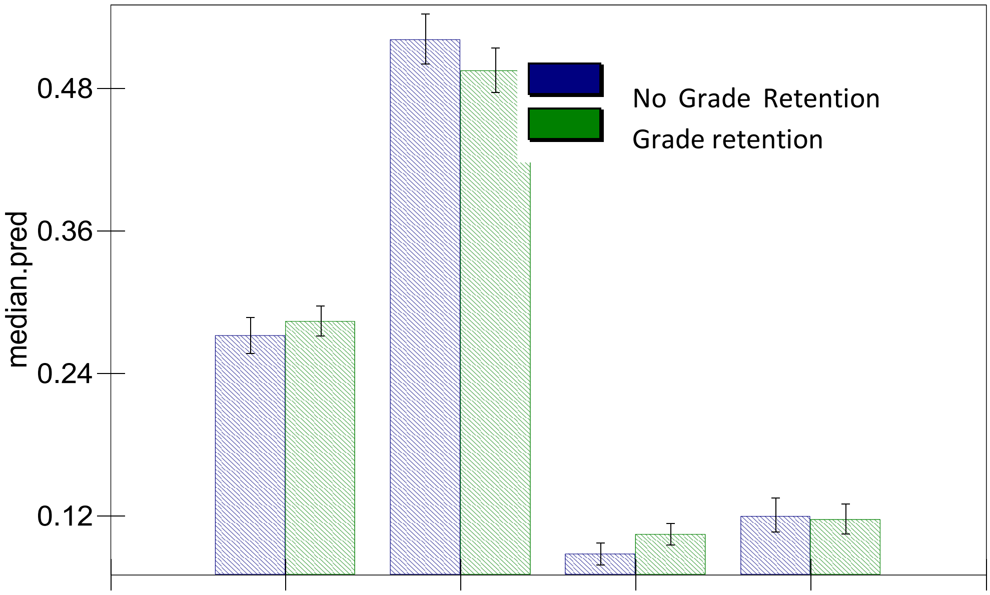
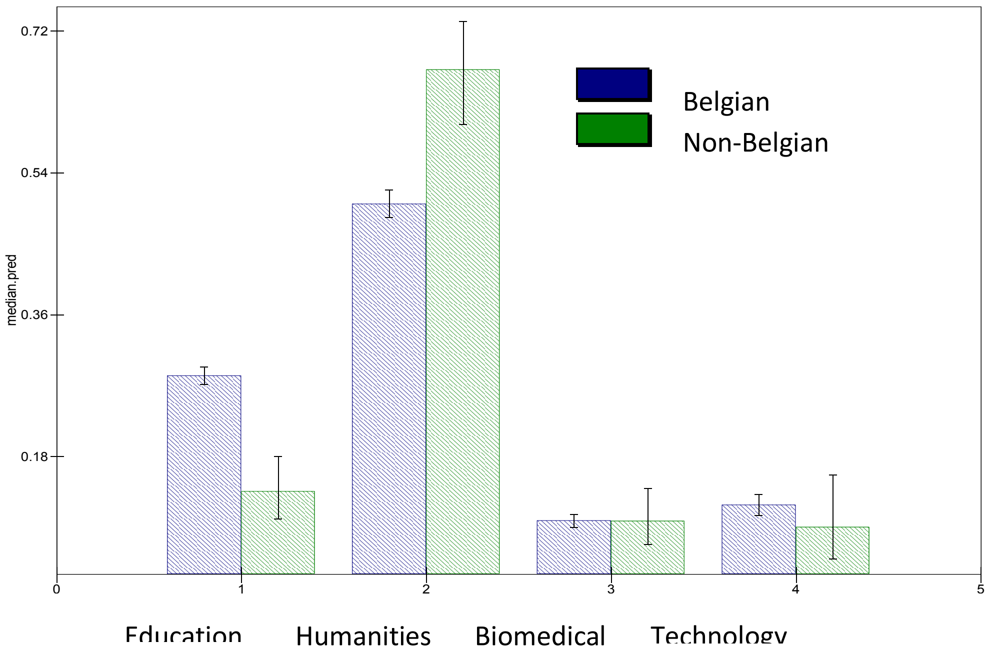


Figure 10 shows the different enrolment probabilities of both Belgian and students from other nationalities.

Figure 10: Predicted probabilities of continuing to a specific professional cluster by nationality

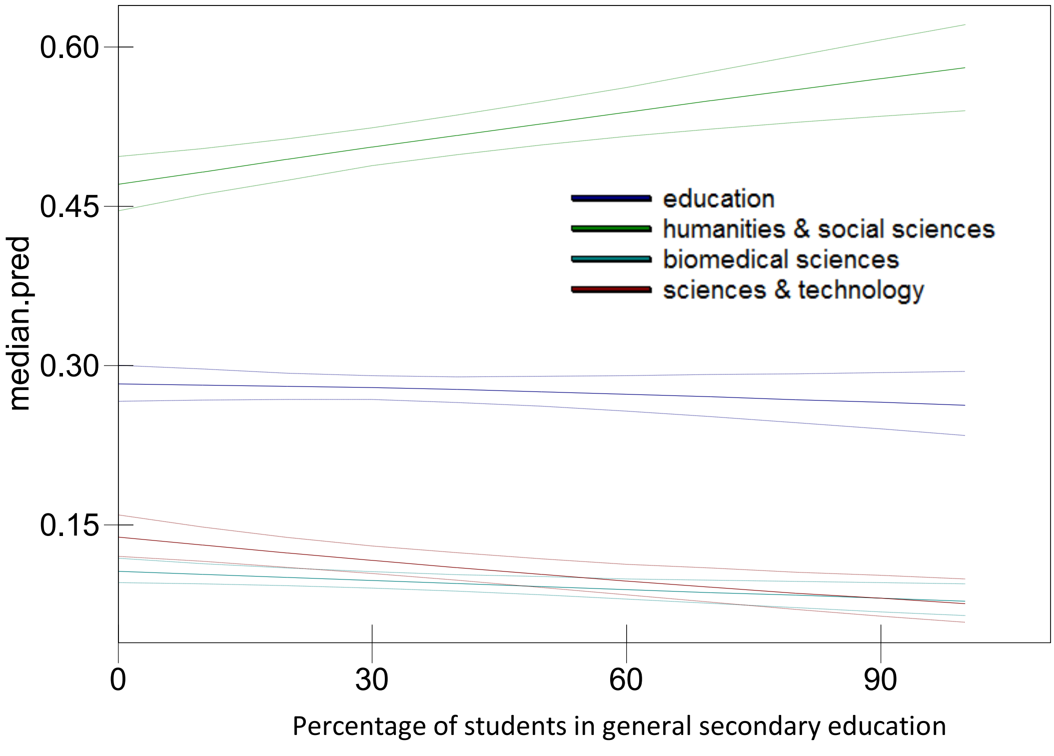


We can see that the enrolment probability in the Education cluster is significantly lower for students with another nationality, while the opposite is true for the Humanities cluster. Nationality does not significantly influence the enrolment probabilities in the Biomedical and Technology cluster.

Interpretation of the variables at the school level

Model 7 in Table 11 showed us the enrolment probabilities of a student in the different professional clusters depend significantly on the percentage of students attending general secondary education in the secondary school he or she attended. Figure 11 visualizes these results. The probability of enrolment of the Humanities and Technology clusters depend on the percentage of general secondary students in a student's secondary school. While a student has a higher likelihood of enrolling in the Humanities cluster when he attended a secondary school with a higher level of general secondary education students, the opposite is true for the Technology cluster. The enrolment probabilities in the Education and Biomedical clusters do not seem to depend on the school composition of the student's secondary school.

Figure 11: Predicted probabilities of continuing to a specific professional cluster by percentage of students in general secondary education



We want to conclude this chapter by enumerating the most important findings. We found the education form profile of the Teacher Education cluster to be quite different from those of the other professional clusters. Vocational secondary education students have a far higher probability to enrol in teacher education programmes. The opposite is true for general and technical secondary education students. We also found the effects of vocational and technical secondary education to vary significantly between secondary schools and argued this might be due to a different offer of trainings and specialisations. We did not find differences in grade retention levels between the professional clusters. The Teacher Education cluster was found to have a very feminine and Belgian character. To conclude, the percentage of general secondary education students in a secondary school was found to increase the probability of a student to enrol in the Humanities cluster, while the opposite is true for the Technology cluster. No effect of this variable on the enrolment probability in the Education and Biomedical cluster was found.

DISCUSSION AND CONCLUSIONS

The aim of this report was to gain more in-depth knowledge in the inflow in professional teacher education programmes in Flanders by comparing the inflow of different levels of higher education. In this chapter, we will summarize the findings and formulate their implications.

We compared the students' profiles of teacher education with three other professional clusters, namely a Humanities, a Biomedical and a Technology cluster. The inflow probability of vocational students in the Education cluster was found to be particularly high compared to the other clusters. This is however solely due to the high enrolment probability of vocational students in nursery teacher education.

Students who enrol in teacher education programmes have a similar profile when considering levels of grade retention, taking into account education forms and other control variables. In this regard, the inflow of students in teacher education cannot be considered as weaker than the other professional programmes in higher education in Flanders. Very few students who do not have the Belgian nationality enrol in teacher education. The feminine character of teacher education is also confirmed in the analyses.

Secondary schools are found to significantly influence the choice between one of the four professional bachelor clusters. An increasing percentage of general secondary education students increases the likelihood of opting for the Humanities cluster, while the opposite is true for the Technology cluster. This variable did however not influence the likelihood of opting for the Education and Biomedical cluster. The importance of this variable seems however very limited, as the unexplained variance at the school level did not decrease substantially.

The differences between secondary schools' enrolment probabilities in the different clusters can largely be explained by allowing the individual effects of the education forms to vary across schools (random slopes model), indicating the effect of the education forms on the probability of enrolment in the different professional clusters does significantly differ between secondary schools. We stated the argument that this is possibly due to different offers of specialisations and trainings in secondary schools. We found for example that for every cluster more than 50 percent of the inflow of vocational students can be attributed to five specialisations. If a secondary school does not offer some of the specialisations that often lead to the transition to a specific cluster, very few students of this secondary school will make this type of transition.

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