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Abstract

Many countries organize their higher education system with limited or no ex ante admission standards. They instead rely more heavily on an ex post selection mechanism, based on the students' performance during higher education. We analyze how a system with ex post selection affects initial enrollment and final degree completion, using a rich dataset for Belgium (region of Flanders). We develop a dynamic discrete choice model of college/university and major choice, where the outcome of the enrollment decision is uncertain. Upon observing past performance, students may decide to continue, reorient to another major, or drop out. We find that ex post student selection is very strong: less than half of the students successfully complete their course work in the first year. Unsuccessful students mainly switch from university to college majors, or from college majors to drop-out. We use the estimates of our model to evaluate the effects of alternative, ex ante admission policies. We find that a suitably designed ex ante screening system (with moderate admission thresholds) can considerably increase degree completion in higher education. A discriminatory screening system for universities only, can raise total degree completion even more, though it implies a shift from university to college degrees.

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1 Introduction

The organization of higher education often involves difficult tradeoffs between the objectives of enrollment and degree completion within a reasonable time. On the one hand, governments aim to ensure broad access to a large number of students. On the other hand, they want to allocate resources efficiently and minimize drop-out or delay by matching students to educational programs according to their skills. A recent policy report (OECD, 2012) illustrates the problems in the organization of higher education: up to 62% of today's young adults in OECD countries enter a university-level program, but only 39% are expected to complete it. Among the students who complete a degree, there is a large fraction that incurs substantial delays.

Several countries have used ex ante screening or admission policies to influence the possible trade-offs between enrollment, completion and efficiency. In the U.S., students are mainly screened ex ante, through admission standards and tuition fees. But admission standards mainly apply to universities and not to the community colleges. In Europe, some countries have also adopted ex ante admission policies, most notably in the U.K. and Ireland. But most other European countries largely select students on an ex post basis: both admission standards and tuition fees are very low, and students are selected based on their performance during their higher education. Belgium, the focus of our empirical analysis, is a prominent example of such an ex post selection system. On the one hand, tuition fees are low and all high school graduates are entitled to start at almost all higher education programs, regardless of their specific high school degree. On the other hand, there is very strong ex post selection especially after the first year of higher education, where many students drop out or switch from university to college majors.

In this paper, we study such a system of ex post student selection to analyze the possible trade-offs between enrollment, completion and efficiency. We develop and estimate a dynamic discrete choice model of college and major choice, where the outcome of the enrollment decision is uncertain. Upon observing past performance, students may decide to continue, reorient to another institution and/or major, or drop out, thereby balancing their current costs and benefits from studying against the future expected benefits on the labor market. We account for the impact of demographics and high school background on choices and study success. We also control for unobserved factors affecting utility and success, and we allow for correlation of these unobserved factors over time by assuming that students are drawn from a finite mixture distribution.[1]

[1] To estimate the model, we use the conditional choice probability (CCP) technique developed by Hotz and Miller (1993) and further refined by Arcidiacono and Miller (2011) to allow for unobserved heterogeneity.

We apply our analysis using rich register data for Flanders, the Dutch-speaking part of Belgium, where there is essentially no ex ante screening and very strong ex post selection (similar to the French-speaking part of Belgium and many other countries). This unique setting of ex post selection allows us to observe the prefered option of students since choices are hardly constrained. All high school graduates can choose almost any program at two types of institutions: colleges (professional orientation) and universities (academic orientation). Success rates after the first year are low (less than 50% after the first year), but highly predictable by student characteristics (such as high school track record). Unsuccessful university students tend to either persist or reorient towards college majors. Unsuccessful college students also tend to either persist or reorient to other college majors, or they drop out from higher education altogether. As a result, less than 40% of the students complete their first three years without delay and many students need up to six years. This implies large losses from mismatching in the form of reorientation or drop-out.

We use the parameter estimates to evaluate the effects of introducing ex ante admission policies. More precisely, we consider the effects of restricting access to study options for students with low predicted first-year success rates. For example, this implies restricting access to sciences majors for students without a sufficient math background in high school, since the model predicts very low success rates for these cases. We consider the effects of such admission policies on both overall educational attainment (the number of students that eventually graduate) and on the relative number of students that graduate without delay. We find that an ex ante screening system with modest admission thresholds can increase overall educational attainment in higher education.

First, we consider a uniform admission standard that applies to both colleges and universities. A modest admission threshold to students with a predicted success rate in study options of at least 28% maximizes overall educational attainment: it reduces the first-year entry rate by 5.5% points, and at the same time it increases overall educational attainment by 1.4% points (+1.7% points at colleges and a negligible –0.3% points at universities). This is because the admission threshold induces a shift from universities to colleges in the first year: students with very low expected success rates will now immediately choose other programs at colleges where they expect higher success rates. In sum, a mild uniform admission standard turns out not to involve any tradeoffs: the number of first-year entrants decreases, but success rates and overall educational attainment increase.

Second, we consider a discriminatory admission standard which only applies to universities and not to colleges with a more professional orientation. This policy would be somewhat closer to the current U.S. system with stronger admission restrictions at universities than at the community colleges[2]. An admission threshold to students with a predicted success rate of at least 42% at university majors turns out to maximize overall educational attainment: it reduces the first-year entry rate by –1.9% points, and raises educational attainment by 2.3% points. However, this increase in educational attainment involves a large shift from universities to colleges: there is a large increase in college diplomas (+3.7% points), which comes at the expense of university diploma's (–1.4% points). In sum, a discriminatory admission standard can also improve efficiency without reducing overall attainment, but it involves trading off university versus college attainment.

Ex ante screening systems of higher education have already been studied extensively in the literature, mainly based on the U.S. system. Important contributions analyzing the choice process under admission policies are for example Arcidiacono (2005), Epple et al. (2006) and Fu (2014). In contrast, there has been only very limited research on the ex post selection systems in various European countries. Closest to our research is a small literature on how financial incentives can influence study duration or time to complete a degree. Garibaldi, Giavazzi, Ichino and Rettore (2012) show how a 1,000€ increase in continuation tuition at Bocconi university (Milan) reduces the probability of late graduation by 5.2% points, without inducing more drop-outs. Gunnes, Kirkeboen and Ronning (2013) show that a restitution of 3,000$ in Norway to students who complete their program on time reduced study delay by between 0.8 and 1.5 semesters.[3] In contrast with these papers, we directly focus on the question how a (partial) shift from ex post selection to ex ante screening can reduce study duration without inducing drop-out.

Another related literature has analyzed first-year participation and study decisions. Static discrete choice models consider the decision of major and institution, and analyze the effect of travel costs and tuition fees on enrollment; see Long (2004), Frenette (2006) and Kelchtermans and Verboven (2010). Dynamic discrete choice models study how students trade off the short-term costs and benefits of studying with the long-term effects, accounting for drop-out and increased future earnings; see Keane and Wolpin (1997), Arcidiacono (2004 and 2005) and Joensen (2009). We combine these literatures and specifically account for uncertainty in the outcome of enrollment under ex post student selection. We also consider much richer choice sets than in current dynamic discrete choice models and incorporate unobserved heterogeneity in both educational choices and study outcomes.

[2] Long and Kurlaender (2009) analyze enrollment at community colleges that offer open and affordable access to tertiary education.

[3] Other studies on financial incentives and time to complete a degree include Hakkinen and Uusitalo (2003) on a financial aid reform in Finland; Heineck, Kifman and Lorenz (2006) on extra tuition fees for delayed students in Germany; and Dynarski (2003) on merit aid programs in Georgia and Arkansas.

The remainder of this paper is organized as follows: Section 2 reviews admission policies in higher education across different OECD countries. Section 3 provides an institutional overview of the higher education system in Flanders, and takes a first look at the rich register data, describing first-year participation, subsequent success and reorientation after the first year. Section 4 then sets up a dynamic discrete choice model, accounting for the key institutional features of the ex post selection system. Finally, section 5 discusses the empirical results and section 6 uses the parameter estimates to analyze the impact of some alternative ex ante admission policies on first-year attendance, study efficiency and overall educational attainment.

2 Admission policies in higher education

Admission policies aim to improve the matching between students and programs. Students base their matching decisions on their preferences, previous background and intrinsic skills. But students may make the wrong matching decisions for a variety of reasons, for example because they do not account for the full educational costs of studying (as is the case when education is subsidized), or because they overestimate or underestimate their talents. Stinebrickner and Stinebrickner (2013) show that students on average overestimate their talents at entrance and that 45% of the drop-out that occurs in the first two years of college can be attributed to what students learn about their academic performance. Admission policies can thus help to improve the matching process, which can reduce drop-out rates, increase the number of graduating students, and increase the speed at which they graduate. Admission policies also have their limitations. For example, they may not be based on sufficiently accurate information about students, or they may be too strict, thereby preventing potentially good matches.

Helms (2011) compares the admission policies in higher education across various countries. He considers the role of examinations, secondary school preparation, application materials and demographic factors. Countries have followed diverse policies concerning the screening and selection of students. Some countries have strict ex ante screening policies, while other countries have weak or no ex ante screening and only have ex post selection. Countries also differ in the level of tuition fees. We can accordingly classify countries in three groups.

The first group of countries mainly selects students ex ante, through both screening policies and tuition fees. An example of this group is the U.S., where institutions set their own admission standards within boundaries set by the states (Cheps, 2011). As a result, not all states have universally adopted admission standards. For example, in Texas and

California, community colleges accept all students qualifying for higher education, while universities set their own admission standards. High school grades and test scores are used as admission criteria and access is guaranteed for the best high school students.[4] Some European countries have also adopted ex ante admission policies. The U.K. has a policy that is closest to the U.S.: universities are free to set their own admission standards and can set relatively high tuition fees subject to a cap.[5] In Ireland, universities set their own admission standards based on high school performance (Li, 2012). Tuition fees vary considerably from around €9,000 up to around €40,000 depending on the program.

A second group of countries has low tuition fees, but still screens students ex ante through admission standards, such as national entry exams or admission criteria set by the universities. For example, in Germany, universities use the final grade in high school as a main admission criterion (Kübler, 2011).[6] Students have to pass a national entry exam for programs in medicine, education and law. In Sweden, universities determine their competence requirements for entry based on high school grades and the results of the Swedish Scholastic Aptitude Test (Cheps, 2011). In Finland (Cheps, 2011) universities select students through entry examinations, and governments restrict entry through a numerus clausus in all programs. In Denmark (Cheps, 2011), admissions are based on grades in high school. The Danish government also determines the maximum number of students in specific fields of study. In Portugal, the government determines a numerus clausus for each program and students are placed according to their preferences and relative marks in the national entrance exam (Cheps, 2008).

Finally, a third group of countries has low tuition fees and no or weak ex ante screening policies, i.e. students with an appropriate high school degree are allowed to start at most higher education programs. In these countries, students are instead selected on an ex post basis, depending on their performance in courses. For example, in Italy, France, Switzerland and Austria, all high school graduates who passed a national exam are eligible to start at most programs at public universities.[7] In the Netherlands, students with an appropriate

[4] In Texas, high school students in the top 10% of their graduating classes are given automatic admission to public universities (Boland and Mulrennan, 2011). The university of California system guarantees eligibility for the top 9% state-wide and the top 9% at each school (Cheps, 2011).

[5] As discussed in Cheps (2011), students have to send an application form that contains high school results, a personal statement and a reference from the applicant's school to each institution for which they want to apply. Institutions also set their own tuition fees, but subject to a cap, currently at £9000 (Li, 2012).

[6] For programs with capacity constraints in German universities, the governement has determined that 20% of study places should be allocated to the best performing high school graduates (Cheps, 2011).

[7] In Italy, students only have to pass an entry exam for programs for which the Italian law imposes a maximum number of students (Merlino and Nicolo, 2012). Private institutions can set their own admission standards. In Switzerland, all study programs that do not have capacity restrictions are open to students

high school degree are allowed to start at all programs where no restrictions on the number of students apply. For programs with a quota, students have to participate in a nationally organized, weighted lottery system.[8]

Table 1 provides an overview of admission policies in OECD countries. We classify the countries in the above three groups according to the main type of screening policy (although specific admission criteria can differ across institutions, programs or regions within the country). For each country, Table 1 shows the first-year enrollment rates (or entry rates), the completion rates and a measure of efficiency.[9] Enrollment rates are defined as the percentage of an age cohort that is expected to enter a university level program (tertiary type A).[10] Completion rates are similarly defined as the percentage of an age cohort that is expected to graduate from a university level program over the lifetime. We calculate efficiency as the ratio of both: the percentage of university-level graduates divided by the percentage of university-level entrants.

Table 1 suggests some interesting preliminary observations. First-year enrollment or entry rates are not necessarily lower in countries with ex ante screening policies (the first and second group). For example, Sweden and the U.S. have the highest entry rates despite ex ante screening policies (and in addition tuition fees in the U.S.). Second, graduation rates also tend to be somewhat higher in countries with ex ante screening, with the highest graduation rates in the U.K., Denmark and Ireland. Third, the efficiency (ratio of graduation over entry rates) also tends to be higher in countries with ex ante screening policies, with the highest efficiency ratios in Ireland, the U.K. and Denmark. Countries with ex post selection policies tend to have lower efficiency ratios. Two exceptions are the U.S. and Sweden, where the efficiency is low despite the fact that these countries follow ex ante screening policies. Efficiency in the U.S. is low, because only the universities set their own admission standards, while community colleges offer open and affordable access to many students (Long and Kurlaender, 2009) These observations suggest that countries with ex ante screening policies achieve higher graduation rates and are more efficient than countries with ex post selection.

who passed the Swiss Matura (Cheps, 2011). In France, all pupils who possess a Baccalauréat are allowed to enroll in university programs (Cheps, 2007). In Austria, pupils who pass the secondary leaving examinations, typically can enroll in university studies of their choice (Helms, 2008).

[8] A weighted lottery system is used for admission to programs with capacity constraints In the Netherlands (Boland and Mulrennan, 2011). All students receive a weight in the lottery, based on the score on the national end exam. The best scoring students are automatically admitted.

[9] Entry and graduation rates are obtained from OECD statistics (OECD, 2012).

[10] Tertiary type A programs are largely theory-based programs designed to provide sufficient qualifications for entry to advanced research programs with high skill requirements. These programs are not exclusively offered at universities (OECD, 2012).

Table 1: Admission policies and study efficiency in university level programs

Admission policy	Countries	Enrollment	Completion	Efficiency
Ex ante screening and tuition fees	U.S.	74	38	51
	U.K.	63	51	81
	Ireland	56	47	84
Ex ante screening but low or no tuition fees	Germany	42	30	71
	Sweden	76	37	49
	Denmark	65	50	77
Ex post selection	Italy	49	32	65
	Switzerland	44	31	70
	Austria	63	30	48
	Netherlands	65	42	65

Note: Enrollment and completion rates are expresses in percentages of an age cohort. Efficiency is calculated as the percentage of university graduates divided by the percentage of university entrants.

Nevertheless, caution is warranted in drawing this conclusion, since the countries differ in several respects and the data definitions are not entirely comparable across countries. In the rest of this paper, we aim to provide more thorough conclusions based on a detailed analysis of Belgium, the region of Flanders, which has an ex post selection system, representative for the the third group of countries.

3 Higher education in Flanders

3.1 Institutional overview

Flanders is the Dutch-speaking part of Belgium, located in the North. It consists of about 60% of the population of 11 million inhabitants, compared with 40% in the French-speaking part, which is located in the South and most of Brussels.[11] Because of the different languages, both higher education systems are quite closed systems, with only a limited number of students attending universities and colleges in the other region. Nevertheless, because of their long common history, both the Dutch-speaking and French-speaking educational system are quite comparable in terms of screening and selection policies. The system is one of ex post selection with no admission standards and low tuition fees. As discussed in Cantillon and Declercq

[11] A small minority of the Dutch-speaking part (about 10%) also lives in Brussels. There is also a small German-speaking part in Belgium, located in the East (about 0.6% of the population)

(2012), all pupils who obtained a high school diploma are entitled to start in most higher education programs, regardless of their specific high school degree (Cantillon and Declercq, 2012). Institutions are not allowed to set their own admission standards. [12] Tuition fees are also low, currently capped at 596.3 EUR in Flanders and 835 EUR in the French-speaking community. Tuition fees in Flanders thus cover only 3% of the total costs of higher education (Cantillon et al., 2006).

Two types of institutions offer higher education programs in Flanders: universities and colleges.[13] Universities offer programs with an academic focus, while colleges mainly offer programs with a vocational focus (professional orientation). Both universities and colleges offer programs in the four majors: sciences (SCI), biomedical sciences (BIOM), social sciences (SSCI) and culture and languages (ARTS). There are five universities, spread throughout the region. They have a large size and offer a wide variety of study programs in all majors. There are many more colleges (about 25), with a broad geographic coverage. They have a considerably smaller size and they tend to specialize in a limited number of study programs, often limited to one or at most two majors.

In sum, both universities and colleges have essentially no autonomy to screen students ex ante, whether through admission standards or through tuition fees. They can however select students ex post, as they have autonomy in giving credits based on students' performance in courses. As a result, student success rates are very low, especially after the first year. Less than 50% successfully complete their required course work after the first year, and there is not only significant drop-out but also substantial reorientation after the first year.

3.2 A first look at the data

In this paper, we use a rich dataset provided by the Flemish Ministry of Education to investigate educational choices, ex post selection and reorientation decisions. We combine two datasets from the Ministry. The secondary school dataset covers 55,524 high school pupils who graduated from high school in 2001 (typically at the age of 18, if they incurred no delay). The higher education dataset covers all students who start with higher education in 2001, followed for a period of six years with information on their performance until they graduate or drop out. As in Kelchtermans and Verboven (2010), we combine both datasets so that we can identify which students start with a higher education and which students immediately start working after completing high school.

[12] The government only imposes entry exams for a very limited number of programs, medicine at universities and some artistic programs at colleges.

[13] We provide a brief overview. For more detailed information of the higher education landscape, see for example Dassen and Luijten-Lub (2007).

In the combined dataset, we observe various personal characteristics, including gender, age, nationality, high school affiliation (catholic or not) and high school study program. There are four types of high school: general, technical, artistic and professional. The general high school type provides a stronger theoretical background, and prepares best for universities. Technical and artistic high schools are more practically oriented, and prepare better towards colleges. Professional high schools are more directly oriented towards the labor market, but pupils can in principle also start any type of higher education degree if they complete one extra preparatory year. As we will see, the distinction between the different high schools is not always clear-cut, and many students from general high school start at colleges and the reverse also occurs (to a lesser extent). We observe the students for a period of up to six years, and assume they graduate after three years of successful coursework. This is equivalent to obtaining a bachelor degree. This is a reasonably accurate description for colleges. For universities, one has to add one or two years of coursework for obtaining the master degree.[14]

First-year enrollment and subsequent success Table 2 shows summary statistics for all 55,524 pupils who finished high school in 2001. The top panel shows first-year enrollment rates (or entry rates) at colleges and universities, broken down by the type of high school previously followed by the pupils (general versus other). 65% of the high school graduates continue to start higher education. More pupils choose college programs (44.1%) than university programs (20.9%). Pupils who graduated from a general high school are most likely to start with higher education (87.3%), and they are comparatively more likely to go to university (44.3%) than to college (43.0%). Pupils who graduated from another type of high school (technical, artistic or professional) are less likely to start higher education (only 46.8), and almost all go to colleges (45.0% versus only 1.8% to universities).

The next panels show success rates after the first year and in subsequent years. After the first year, only 31.6% of high school graduates successfully complete their required course work for that year. This is less than half of the 65.0% participating students. After three years of studying, only 25.0% of the high school graduates have obtained their diploma in time, which is less than 40% of the initially enrolled students. After six years[15], 43.6% of the high school graduates have obtained their diploma, which is about 67% of the participating students. This is similar to the efficiency ratios of most other countries with an ex post selection system presented in Table 1 (Italy, the Netherlands and Switzerland).

[14] The year 2001 was before the actual bachelor-master reform, but the total length of study remained the same after the reform.

[15] 2.1% of the students have not obtained a degree in higher education after 6 years of studying. We assume that they drop out of education after period 6. This leads to some right censored observations.

It is also interesting to consider the break-down of success by universities and colleges, and by type of high school. Pupils with a general high school are considerably more successful. For example, 49.3% out of 87.3% general high school students successfully complete the first year in time, compared to only 17.0% out of 46.8% of the students from other types of high school (technical, artistic and colleges). General high school students are also considerably more likely to obtain their diploma within the required three years or after six years.

Table 2: Enrollment and success in higher education

	university	college	total
Enrollment			
All students	20.9	44.1	65.0
General HS	44.3	43.0	87.3
Other HS programs	1.8	45.0	46.7
Success after 1 year			
All students	10.8	20.8	31.6
General HS	23.7	25.6	49.3
Other HS programs	0.2	16.8	17.0
Diploma after 3 years			
All students	9.3	15.6	25.0
General HS	20.5	20.2	40.7
Other HS programs	0.2	11.9	12.1
Diploma after 6 years			
All students	13.8	29.8	43.6
General HS	30.1	39.7	69.7
Other HS programs	0.4	21.7	22.2

Note: Percentage of high school graduates who choose for each option, based on own calculations

Success rates are also lower at colleges than at universities, but the difference is not that large. For example, after the first year 10.8% out of 20.9% of the university students are successful, compared with 20.8% out of 44.1%. However, behind these numbers there are extremely large differences between general high school students and other high school students. General high school students have a more than 50% success rate after the first year: 23.7/44.3=53.5% at universities, and 25.6/43.0=59.5% at colleges. Students from other high school types have much lower success rates after the first year: only 16.8/45.0=37.0% at colleges, and an extremely low 0.2/1.8=11.1% at universities. Similar conclusions hold for success rates after 3 years and 6 years.

Table A1 in Appendix 2 provides more detailed information on the role of student characteristics (gender and delay during high school) and high school background (a break-down of general high school in 7 groups, according to an orientation into mathematics, sciences, classical languages, modern languages, economics and humanities; and a break-down of technical high schools in sciences, technology, management and other areas). We discuss the role of these variables with some examples here. Males are less likely to start with higher education (only 59.3%, compared with 70.4% of females). The gap between males and females is even larger when looking at success rates: only 36.3% of males obtain their diploma after six years, compared with 50.6% of females. Similarly, students who started education with one year of delay (i.e. one year older than the usual 18) are less likely to participate in higher education, and less likely to graduate, especially at universities. As a final example, students who took mathematics or classical language within a general high school type, have the highest participation rates, especially at universities, and they also have the highest graduation rates.

Reorientation in higher education During higher education, students may switch to another program, especially if they were unsuccessful. Table 3 describes the number of graduating students in specific majors (columns) as a percentage of the number of students who started that major (row). This gives an indication of the importance of switching behavior. According to the first row, 66.9% of all participating students obtain a degree in higher education. More students obtain a degree at colleges, especially within the major of social sciences.

According to the subsequent rows, a majority of graduating students remain within their major, but there is also substantial reorientation. Consider for example the second row, which describes the outcomes of students who start a major in sciences at a university. 84.9% of these students graduate, and a majority of 60.9% obtains the initially chosen major. But an important fraction of 18.3% switches to obtain a college degree (especially in sciences or social sciences). And a smaller fraction of 5.7% switches to another university major (mainly biomedical sciences).

We observe similar switching patterns from other university majors. Most university students eventually graduate within their initially chosen university major (diagonal in top left panel). But an important fraction of 18.0% switches to colleges, especially to the twin college major (diagonal in top right panel). The reverse occurs much less frequently: only 0.6% of the students who started at a college major obtain a diploma at a university (bottom panel of Table 3). Students who started at a college major are more likely to switch to another college major (if they do not drop out). The much stronger switching from universities to colleges than vice versa reflects a "cascade effect": students start in the more difficult majors and update their choices depending on their successes. This ability sorting is also confirmed by Arcidiacono (2004) and Stinebrickner and Stinenbrickner (2013).[16] Table A2 in Appendix 2 illustrates that ability sorting is particularly strong after the first year in higher education. We show that a substantial fraction of the students who do not succeed for all courses in the first year of the program switch to another program or drop out of higher education.

Table 3: Reorientation and completion in higher education

Choice in	University degree					College degree					Total
period 1	SCI	BIOM	SSCI	ARTS	Total	SCI	BIOM	SSCI	ARTS	Total	degree
All students	3.6	4.6	9.6	3.3	21.1	8.6	5.1	29.9	2.2	45.8	66.9
University											
SCI	60.9	2.8	2.2	0.7	66.6	8.3	1.7	8.0	0.3	18.3	84.9
BIOM	1.4	67.1	1.7	0.8	71.0	2.2	7.7	6.2	0.2	16.3	87.3
SSCI	0.1	0.4	59.9	0.8	61.2	0.9	0.9	17.2	0.4	19.4	80.6
ARTS	0.0	0.1	2.3	61.9	64.3	0.6	0.4	12.8	2.0	15.8	80.1
Total	11.1	14.1	29.3	10.0	64.5	2.4	2.3	12.7	0.6	18.0	82.5
College											
SCI	0.1	0.2	0.5	0.2	1.0	53.2	1.3	5.0	0.5	60.0	61.0
BIOM	0.0	0.2	0.1	0.1	0.4	1.0	53.9	5.7	0.1	60.7	61.1
SSCI	0.0	0.0	0.1	0.1	0.2	0.7	0.7	57.0	0.2	58.6	58.8
ARTS	0.1	0.2	1.2	0.6	2.1	1.0	0.6	14.5	42.9	59.0	61.1
Total	0.1	0.1	0.3	0.1	0.6	11.6	6.4	38.1	3.0	59.1	59.7

Note: The percentage of graduates in each major (columns) is expressed relative to the number of students who start in each particular major (rows).

We can summarize this discussion as follows. The system of low tuition fees without any ex ante screening procedures does not appear to have encouraged entry into higher education, and has led to a low study efficiency. Only 65% of the pupils who obtained a high school diploma start with higher education, and less than 40% of these participating students complete their first three years within the foreseen time. A larger, but still not very impressive fraction of 67% eventually completes the first three years (within six years

[16]Note that because of this switching behavior it is possible that the number of graduates in a major is larger than the number of starting students (as seen in Table A1 of Appendix 2). This will occur for students who start at colleges and have a strong high school background (such as mathematics). Because of the ability sorting, many students who started at universities with the same high school background will reorient and switch to the college major.

of study). Many students switch to other majors or drop out during their study path. Switching especially occurs from university to college majors, and drop-out especially occurs from colleges. These findings suggest that there is room for improvement. In the next sections, we develop and estimate a dynamic discrete choice model to assess whether this is the case.

4 Empirical framework

We set up a dynamic discrete choice model of educational choice. We first provide a brief overview of the model within the institutional set-up. We then develop the dynamic choice model in more detail. Finally, we discuss estimation and how we extend the model to account for unobserved heterogeneity. We use the conditional choice probability (CCP) approach developed by Hotz and Miller (1993) and further refined by Arcidiacono and Miller (2011) to account for unobserved differences in ability and educational benefits/costs.

4.1 Overview

Our model closely follows the institutional environment as described in the previous section. In each year $t = 1, \ldots, T$, students choose one of the available alternatives $j = 0, \ldots, J$. A study option $j = 1, \ldots, J$ refers to one of the four possible majors (SCI, BIOM, SSCI or ARTS) at five possible universities or at the nearest college. The option $j = 0$ refers to the decision to drop out and enter the labor market.[17]

Students have to accumulate three credits (=years of coursework) to obtain their diploma. Credit accumulation is uncertain, and follows a simple law of motion: at the end of period t, the number of accumulated credits is $X_{t+1} = X_t + 1$ if the student is succesful, and $X_{t+1} = X_t$ if she fails. If students have accumulated 3 credits, they enter the labor market and earn wages according to their obtained diploma. If students drop out before accumulating 3 credits, they also enter the labor market and earn the drop-out wage.

The specific timing therefore works as follows:

1. In period $t = 1$, each high school graduate can choose any study option $j = 1, \ldots, J$, or the drop-out option $j = 0$. At the end of period 1, a student observes her performance, i.e. whether she successfully accumulated 1 credit.

[17] Since one of the five universities does not offer ARTS as a major, the total number of study options is 24 (1 drop-out option, 19 options at universities, and 4 options at colleges).

2. In subsequent periods $t > 1$, students decide whether to continue their program, to switch to another program, or to drop out, conditional on the observed performance at the end of period $t-1$. At the end of period t, a student again observes her performance.

3. If a student has succesfully accumulated 3 credits, she obtains her diploma, starts working and earns the wage corresponding to the obtained degree. If she drops out before accumulating 3 credits, she starts working and earns the drop-out wage.

4.2 Dynamic choice model

4.2.1 Flow utility and credit accumulation

Flow utility In each year t, a student chooses an option $j = 0, \ldots, J$, where $j = 0$ is the drop-out option and the remaining $j > 0$ are the various study options. A student's decision in period t is given by $d_t = \left(d_t^0, d_t^1, \ldots, d_t^J\right)$, where d_t^j is a dummy variable equal to 1 if the alternative is chosen and 0 otherwise.[18] The flow utility of a study option $j > 0$ in period t consists of the current consumption value and costs (distinct from future benefits in the form of increased earnings after obtaining a diploma). This flow utility is given by

$$u_t^j(S_0, C^j, X_t, d_{t-1}) = \alpha_1^j S_0 + \alpha_2 C^j + \alpha_3 X_t + \alpha_4^j d_{t-1} + \varepsilon_t^j. \tag{1}$$

A student's flow utility in period t thus depends on a vector of time-invariant student characteristics S_0, such as gender and high school background. It also depends on travel costs C^j, given by the distance between the student's location and the location of option j. Furthermore, a student's utility may depend on the number of accumulated credits X_t at the start of period t. This is related to Arcidiacono (2004), who allows utility to depend on the study result of the previous period. A student's utility in addition depends on the option chosen in the previous period, d_{t-1}. This allows for switching costs from taking a major that is different from the previously taken one. Joensen (2009) also includes the option chosen in the previous period as a determinant of utility. We will allow switching costs from and to any major to be different. This is more general than Arcidiacono (2004), who assumes that switching costs are the same regardless of the origin of the switching. Finally, utility depends on an error term ε_t^j, which is i.i.d. across individuals and options, according to the distributional assumptions of the logit model.

The flow utility of the drop-out option $j = 0$ depends on the drop-out wage, given the individual's characteristics. We normalize the other utility components in the drop-out option to zero, so that $u_t^0(S_0) = \alpha_5 w_t^0(S_0) + \varepsilon_t^0$.

[18] To simplify notation we omit the subscript for an individual student.

Credit accumulation Credit accumulation is uncertain, and follows a simple law of motion. Prior to education, the number of accumulated credits is $X_0 = 0$. At the end of period $t = 1, \ldots, T$, the number of accumulated credits is $X_{t+1} = X_t + 1$ if the student is succesful and $X_{t+1} = X_t$ if she fails. The probability of success is $\lambda_t^j(S_0, X_t, t)$, which depends on individual characteristics S_0, on previously accumulated credits X_t and on the number of study years t. The probability of success may differ between programs, hence the superscript j.

If students have accumulated $\overline{X}$ credits, they enter the labor market and earn wages $w^j\left(S_0\right)$ according to their obtained diploma j and individual characteristics S_0. If students drop out before accumulating $\overline{X}$ credits, they also enter the labor market and earn the drop-out wage $w^0\left(S_0\right)$. In our application, we consider $\overline{X} = 3$, so we assume a diploma is obtained after the first three years, corresponding to the Bachelor's degree.[19]

4.2.2 Optimization problem

We assume that individuals choose an option j in every period t to maximize the present discounted value of their lifetime utilities, using a discount factor β. To simplify notation, define $\Phi_t = (S_0, C^j, d_{t-1}, t)$ as the vector of state variables in period t observed by the econometrician (as opposed to the state variables $\varepsilon_t = \left(\varepsilon_t^0, \ldots, \varepsilon_t^J\right)$ that are only known to the individual). To model the dynamic optimization problem, the starting point is the individual's conditional value function, i.e. her value function conditional on choosing option j. In our set-up, the conditional value function for a given study option $j = 1, \ldots, J$ is given by

$$V_t^j(\Phi_t, X_t) = u_t^j(\Phi_t, X_t) + \beta \left[\lambda_t^j \widetilde{V}_{t+1}(\Phi_{t+1}, X_t + 1) + (1 - \lambda_t^j)\widetilde{V}_{t+1}(\Phi_{t+1}, X_t)\right], \qquad (2)$$

where $\widetilde{V}_{t+1}(\Phi_{t+1}, X_t)$ and $\widetilde{V}_{t+1}(\Phi_{t+1}, X_t + 1)$ represent the expected value functions, the continuation value of behaving optimally from period $t + 1$ onwards when respectively X_t and $X_t + 1$ credits have been accumulated. Intuitively, the value of choosing option j in period t is equal to the sum of two components: the direct flow utility of choosing option j in period t and the discounted expected future value. This expected future value, in turn, depends on the probability of successful credit accumulation. With probability $\lambda_t^j(S_0, X_t, t)$ the individual successfully accumulates an extra credit and receives a continuation value $\widetilde{V}_{t+1}(\Phi_{t+1}, X_t + 1)$. With probability $1 - \lambda_t^j(S_0, X_t, t)$ the individual is not succesful and receives a continuation value $\widetilde{V}_{t+1}(\Phi_{t+1}, X_t)$.

The conditional value function for $j = 0$ is much simpler because it is a terminal action.

[19] In practice, almost all students continue with a Master degree. There is however very limited switching after three years, so that incorporating this would have only limited impact on the analysis.

If $j = 0$ because of drop-out before graduation ($X_t < \overline{X}$), the student earns the drop-out wage, so her conditional value function is

$$V_t^0(\Phi_t, X_t) = \alpha_5 \sum_{t=1}^{T} \beta^{t-1} w_t^0(S_0), \tag{3}$$

where $T = 40$ is the number of years the individual works after dropout. If instead $j = 0$ because the student has obtained a diploma ($X_t = \overline{X}$), the student earns the wage according to her obtained diploma, so

$$V_t^0(\Phi_t, \overline{X}) = \alpha_5 \sum_{t=1}^{T} \beta^{t-1} w_t^j(S_0),$$

when her previous period choice d_{t-1} was option j (so that she obtained a diploma for option j).

As in Rust (1987) we assume that the unobserved factors are independently and identically type 1 extreme value distributed. For the moment, we also impose the conditional independence assumption. This assumption implies that the unobserved state at t has no effect on the observed state at $t + 1$ after controlling for both the decision and the observed state at t. In the last subsection, we will relax this assumption to allow for unobserved factors to influence utility and success and for serial correlation of these unobserved effects, following Arcidiacono and Miller (2011). Under these assumptions there is a closed form solution for the expected value function, known as the logsum formula (McFadden, 1979):

$$\widetilde{V}_{t+1}(\Phi_{t+1}, X_{t+1}) = \gamma + \log \left[\sum_{j=0}^{J} \exp(V_{t+1}^j(\Phi_{t+1}, X_{t+1})) \right], \tag{4}$$

where γ is Euler's constant and either $X_{t+1} = X_t$ (no successful credict accumulation) or $X_{t+1} = X_t + 1$ (successful credit accumulation). Furthermore, there is an analytic expression for the probability that an individual chooses an option j in period t:

$$\Pr(d_t^j = 1 | \Phi_t, X_t) = \frac{\exp(V_t^j(\Phi_t, X_t))}{\sum_{j=0}^{J} \exp(V_t^j(\Phi_t, X_t))}. \tag{5}$$

In principle, these dynamic choice probabilities (5) can be taken to the data, after substituting (4) into (2), and (2) into (5), i.e. after substituting the expected value functions $\widetilde{V}_{t+1}(\Phi_{t+1}, X_t)$ and $\widetilde{V}_{t+1}(\Phi_{t+1}, X_t + 1)$ into the conditional value functions, and substituting these in turn into the choice probabilities.

4.2.3 CCP representation of the expected value function

In practice, the computation of the dynamic choice probabilities (5) creates a dimensionality problem, because one must determine the expected payoffs for all possible future choice paths. Following Hotz and Miller (1993), we address this problem by representing the expected value function in terms of future conditional choice probabilities (CCPs). These CCPs can then be treated as data instead of as functions of the underlying parameters.

In our institutional set-up, the CCP approach to computing the expected value function simplifies, and it only requires one-period-ahead choice probabilities. This is because individuals can always choose a terminal action at which point the decision problem is no longer dynamic; see also Arcidiacono and Ellickson (2011) for a detailed discussion. This terminal action is drop out before graduation, after which the student earns the drop-out wage according to $V_t^0(\Phi_t, X_t)$ as given by (3). To compute the expected value function with a one-period ahead probability, the key preliminary step is to write the probability that the student chooses to drop out at period $t+1$ before obtaining a diploma:

$$\Pr(d_{t+1}^0 = 1|\Phi_{t+1}, X_{t+1}) = \frac{\exp\left(V_{t+1}^0(\Phi_{t+1}, X_{t+1})\right)}{\sum_{j=0}^{J}\exp(V_{t+1}^j(\Phi_{t+1}, X_{t+1}))}.$$

We can rearrange this and take logarithms, to substitute the logsum term into (4). This gives the following expression for the expected value function:

$$\widetilde{V}_{t+1}(\Phi_{t+1}, X_{t+1}) = \gamma + V_{t+1}^0(\Phi_{t+1}, X_{t+1}) - \log\left(\Pr(d_{t+1}^0 = 1|\Phi_{t+1}, X_{t+1})\right), \tag{6}$$

where $V_{t+1}^0(\Phi_{t+1}, X_{t+1})$ is given by (3) and $\Pr(d_{t+1}^0 = 1|\Phi_{t+1}, X_{t+1})$ can be interpreted as the empirical hazard rate of drop-out, which can be estimated from the data. Hence, the complicated expression for the value function (4) has been simplified into (6), which only depends on the drop-out payoffs in a terminating state and on an adjustment term that depends on the empirical hazard rate of drop-out. We can then substitute (6) (instead of (4)) into (2), and substitute (2) into (5) to compute the choice probabilities that can be taken to the data.

In Appendix 1, we summarize the details of these substitutions, distinguising between two possible cases: (1) $X_t < \overline{X} - 1$, i.e. periods where the student does not yet have a chance to graduate, and (2) $X_t = \overline{X} - 1$, periods where the student has a chance to graduate (with probability λ_t^j).

4.3 Estimation

4.3.1 Basic model

The assumptions of Rust (1987) imply that there is no unobserved heterogeneity in the model and no serial correlation of the unobserved factors.

An individual i's contribution to the log likelihood function in period t $\ln L_{it}(\alpha, \theta)$ then becomes additively separable and equal to the sum of the log likelihood contribution of college and major choices $\ln L_{1it}(\alpha)$ and the log likelihood contribution of success $\ln L_{2it}(\theta)$. The log likelihood function (7) is given by:

$$\ln L(\alpha, \theta) = \sum_{i=1}^{N} \sum_{t=1}^{T} \ln \left(L_{1it}(\alpha) + \ln L_{2it}(\theta) \right), \tag{7}$$

where $L_{1it}(\alpha)$ is given by the choice probabilities (5) and $L_{2it}(\theta)$ is given by the success probability $\lambda_{it}^{j}(S_0, X_t, t)$.

Because of the additive separability of the likelihood function, we can estimate the model in a 2-step procedure as described in Arcidiacono and Miller (2011). In the first step, we predict wages, success probabilities and the probability of drop-out for each student in each state. First, we use an OLS regression to predict the wage path for each individual with all options j (including the drop-out option). We use a dataset about wages in Flanders and assume that students expect their wages to be the same as observed wages of workers with similar characteristics. Second, we predict the success probabilities for each student in each possible state based on a flexible binary logit specification with a larger number of variables and interactions. Third, we predict the conditional probabilities of choosing the drop-out option in each state for all students with a flexible binary logit model (as a hazard rate model). In the second step, we then use the estimation results of the first stage to compute the choice probabilities using the CCP approach with one-period ahead probabilities of drop-out as adjustment term, as discussed above with additional details in Appendix 1. By applying the CCP approach, estimating the dynamic discrete choice model reduces to estimating a static discrete choice model with a correction term.

4.3.2 Extension to unobserved heterogeneity

The basic model incorporates a rich set of student characteristics, but there may still be unobserved factors determining student preferences and success and these factors may be correlated over time. For example, students with an unobserved high preference for sciences in the first period may also have a high preference for sciences in the following periods. To account for such unobserved heterogeneity, we follow Arcidiacono and Miller (2011) and assume there exists a fixed number M of student types, who differ in preferences and success rates. Let π_m be the probability that a student belongs to type m. An individual i of type m in period t has a choice probability $L_{1imt}(\alpha)$ and a success probability $L_{2imt}(\theta)$, where some of the parameters may be specific to her type. We then obtain the following log likelihood function (8)

$$\ln L(\alpha,\theta)=\sum_{n=1}^{N}\ln\left(\sum_{m=1}^{M}\left(\pi_m\prod_{t=1}^{T}\left(L_{1imt}(\alpha)\times L_{2imt}(\theta)\right)\right)\right) \tag{8}$$

The log likelihood function is no longer additively separable. We can use the Expectations Maximization (EM) algorithm to estimate the model. This algorithm consists of 2 steps. In the first step, we take as given the probability π_m that an individual belongs to type m, and we maximize the likelihood with respect to the parameters α and θ. In the second step, we update the probability that individual i belongs to type m by using the likelihood function. We repeat this procedure until convergence.

To estimate the model, we have a very large number of observations: 55,524 high school pupils who can choose between 24 study options (including the no-study option) during up to 6 periods. We also include a large number of variables, and the unobserved heterogeneity parameters. To make estimation manageable, we randomly sample 60% of the pupils.

5 Empirical results

In this section, we discuss the estimates of the model. We first discuss our empirical findings on wages and success probabilities. While these results are of stand-alone interest, they mainly serve as building blocks for our dynamic discrete choice model, which we discuss in the second part of this section.

5.1 Wages and success

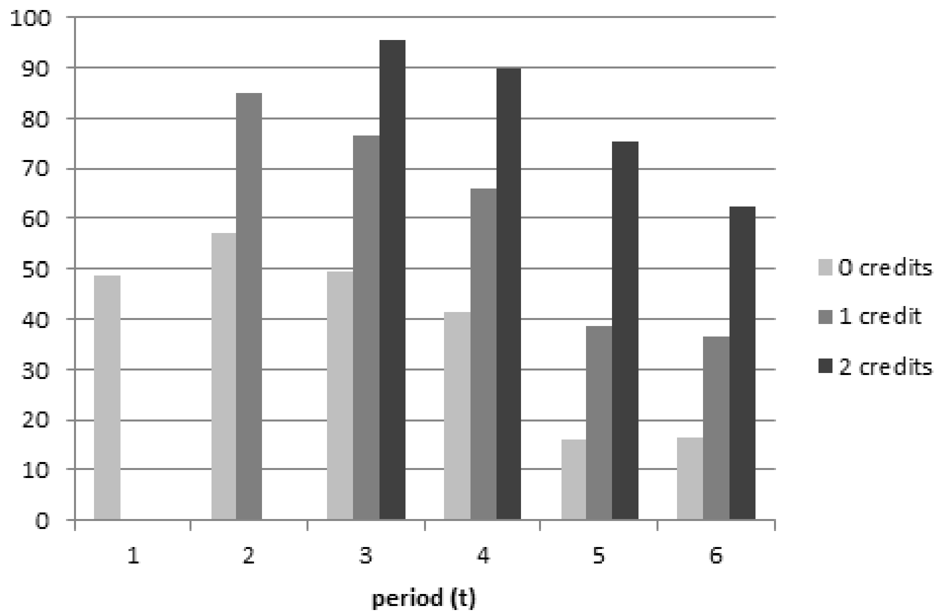
Wages Wages affect student decisions in two ways in our model. First, they directly enter the drop-out payoffs, through the future drop-out wage profile $w_t^0(S_0)$. Second, they enter the payoffs when the student graduates, through the wage profile $w_t^j(S_0)$ after obtaining a diploma for study option j. To estimate future wages under alternative diplomas, we make use of a large survey dataset, "Vacature salarisenquete", containing information for 37,434 workers in Flanders in 2006. We observe gross wages, diploma, municipality, personal characteristics of the workers and years of experience. We use this information to predict the wages of students for each possible diploma. Region dummies serve as an exclusion restriction, i.e. these variables only affect wages and do not directly affect the utility of attending college or university. We obtain the following intuitive findings represented in Table A3 in Appendix 2. Workers with a college or university degree earn on average significantly more than workers without a degree in higher education. Wage premiums are significantly higher for university graduates than for college graduates, and for workers with a degree in the fields of sciences or biomedical sciences at university (as compared with social sciences or arts). Males earn on average higher wages. Finally, wages increase with years of experience (seniority), and this increasing wage path differs across study options.

Success rates The success probabilities $\lambda_t^j(S_0, X_t, t)$ affect student decisions, because they influence the likelihood and the speed at which students obtain a diploma and earn a higher wage. To obtain these probabilities we estimate a binary logit model for success, accounting for unobserved heterogeneity by including two discrete types. We estimate the model based on all students in our main dataset, which we discussed earlier in section 3. We consider a flexible specification, including the following determinants: the number of previously accumulated credits X_t, the year of study t and a rich set of personal and high school background characteristics interacted with all possible study options. We also include the network of the student's high school (catholic versus state), which serves as an exclusion restriction: it may affect the success rate at university or college, but does not directly affect study decisions.

We briefly summarize the main results here, and present the complete set of results in Table A4 of Appendix 2. Based on the parameter estimates, Figure 1 summarizes how the success probabilities vary with the number of credits (or successful years) X_t, and with the number of years of delay $t - X_t$. The histogram shows that success rates are especially low in the first year (less than 50%). Success rates are higher for students without study delay in periods 2 and 3 (approximately 90%). Success rates decrease with the number of years of delay.

Several personal characteristics play an important role in predicting success rates. Males and students who complete high school with at least one year of delay have significantly lower success rates in all options. Students from a catholic high school are more likely to succeed. High school background also predicts the success probability in higher education: students with a general high school background have significantly higher success rates at all programs than students from technical, artistic or vocational high schools. The specific program within a general high school also plays an important role: programs with mathematics, classical languages or sciences imply much higher success rates. Finally, we find that there is unobserved heterogeneity (as modeled through different intercepts for the program options for two types): type 1 individuals have significantly higher success rates in all program options except at arts programs at college. This effect is stronger for university than for college programs. One might therefore interpret the type 1 individuals as "academic types". We return to this interpretation when discussing the results from the dynamic discrete choice model.

Figure 1: Success probabilities in each period



5.2 Dynamic discrete choice model

We now turn to the empirical results of our dynamic discrete choice model, i.e. the parameters that enter the choice probabilities $\Pr(d_t^j = 1|\Phi_t, X_t)$ for the various options j, as a function of the number of previously accumulated credits X_t, and the other state variables $\Phi_t = (S_0, C^j, d_{t-1}, t)$, i.e. time-invariant personal characteristics S_0, previous period choice d_{t-1}, and travel cost C^j. The vector of personal characteristics S_0 consists of gender, delay in high school and high school background characteristics. We set the discount factor $\beta = 0.95$, similar to other studies. As discussed in the model section, we normalize the utility of the drop-out option to zero (with the exception of the drop-out wage), so the parameter estimates should be interpreted relative to the drop-out option as the reference category.

Table 4 shows the empirical results. Because the model has a large number of parameters, Table 4 only shows the parameters relating to the unobserved type alternative specific constants, previously accumulated credits X_t, travel cost C^j, earnings and previous period choices d_{t-1} (capturing switching costs). To save space, Table 4 does not show the estimated effects of the personal characteristics on the utility of the four university and college majors (which amount to 9 demographic variables interacted with 4 majors at university and 15 demographic variables interacted with 4 majors at college). We will briefly discuss these here, and refer to Table A5 in Appendix 2 for the complete set of results.

Table 4 shows that it is important to control for unobserved heterogeneity. From the intercepts for the program options, we see that type 1 individuals obtain more utility from studying than type 2 individuals. This effect is stronger for university programs than for college programs. In the previous section, we already saw that type 1 individuals have higher success rates in all options. Type 1 can thus be interpreted as the academic type. They are more likely to participate in higher education and they also have higher success rates. This interpretation is similar as in Arcidiacono (2004) and Joensen (2009).

Students are highly sensitive to travel distance C^j, consistent with earlier findings of Kelchtermans and Verboven (2010) for first year students. Students also positively value future expected wages upon graduation. Furthermore, good performance increases the utility of continuing higher education: the more credits X_t a student already has obtained, the more likely she will continue at a college or university major. This is consistent with Arcidiacono's (2004) findings for the U.S. Finally, there are significant switching costs (as captured by d_{t-1}), and they differ between the several options. They are the highest for students who want to switch from college to university, and the lowest for students who switch from university to college (with the same major). Switching to other majors is also costly. Switching to social sciences is least costly, while switching to sciences is usually most costly.

We also briefly comment on the role of personal characteristics in educational choice (α_1^j, shown in Appendix). Male students have a strong preference for scientific programs, while female students prefer programs in biomedical sciences. High school background also influences the utility of studying. Pupils with a general high school degree are much more likely to start higher education, especially at universities instead of colleges. Pupils with a mathematical high school background have a strong preference for sciences and biomedical sciences. Pupils with a technical or artistic high school degree are more likely to start at colleges as compared with pupils with a vocational high school degree.

Table 4: Dynamic discrete choice model

Variables		Coef.	St. error	Coef.	St. error
Unobserved type alternative-specific constants					
		type 1		type 2	
SCI UNIV		-4.820*	(0.104)	-9.854*	(0.130)
BIOM UNIV		-4.362*	(0.111)	-9.175*	(0.131)
SSCI UNIV		-3.283*	(0.072)	-6.872*	(0.086)
ARTS UNIV		-3.431*	(0.085)	-7.774*	(0.112)
SCI COLL		-3.718*	(0.101)	-5.750*	(0.107)
BIOM COLL		-3.593*	(0.121)	-6.060*	(0.129)
SSCI COLL		-1.949*	(0.047)	-2.912*	(0.045)
ARTS COLL		-4.492*	(0.135)	-6.411*	(0.143)
type m probability (π_m)		39.3%		60.7%	
Utility parameters					
student characteristics (α_1^j)		included, see table A5			
travel distance (α_2)		-0.298*	(0.003)		
credits (α_3)		1.955*	(0.024)		
earnings (α_5)		0.005*	(0.000)		
Switching parameters (α_4)					
d_t^j	d_{t-1}^j				
SCI	BIOM	-4.238*	(0.096)		
	SSCI	-4.253*	(0.073)		
	ARTS	-4.626*	(0.139)		
BIOM	SCI	-3.075*	(0.086)		
	SSCI	-3.750*	(0.069)		
	ARTS	-5.217*	(0.213)		
SSCI	SCI	-2.558*	(0.050)		
	BIOM	-3.371*	(0.050)		
	ARTS	-2.859*	(0.054)		
ARTS	SCI	-3.147*	(0.127)		
	BIOM	-4.434*	(0.189)		
	SSCI	-3.460*	(0.077)		
UNIV	COLL	-5.436*	(0.072)		
COLL	UNIV	-0.470*	(0.034)		
β		0.95	(0)		

Note: Sample of 60% of 55,524 high school graduates, 24 choice alternatives, up to 6 periods

* statistical significance at 5% level.

^{c} Base category = same option in the previous period

6 Counterfactual analysis

We use the estimates of our model to evaluate the effects of alternative, hypothetical admission policies in higher education. Before performing our policy counterfactuals, we assessed how well the model predicts the actual outcomes, and we found it does reasonably well, as shown in the top two panels of Table 5. For example, 65.0% of the high school students enroll in higher education, while the model predicts 65.1%. Similarly, 31.6% of the high school students successfully completed the first year and 25.0% obtain their diploma within three years, while the model predicts 30.4% and 22.2%, respectively.

We then considered two policy counterfactuals to assess the effects of introducing admission standards. Our first policy counterfactual considers an admission standard that is uniform across all programs. Our second policy counterfactual considers a discriminatory admission standard that only applies to universities (where success rates are lower) and not to colleges.

Generally speaking, raising admission standards involves the following possible trade-off. On the one hand, it reduces first-year enrollment, but on the other hand it induces students to shift to other programs, where they have higher success probabilities. As a result, increasing the admission standard reduces initial enrollment, but it may increase the number of students who succesfully obtain their degree after three years or after six years. After outlining our approach (subsection 6.1), we show the effects of raising admission standards on overall educational attainment (subsection 6.2). Finally, we focus on the optimal admission standards (which maximize overall educational attainment) to assess how this induces shifts from university to college programs (subsection 6.3).

6.1 Approach

There are several ways in which one may implement the admission standards. A first approach would be to base admission standards on high school background, e.g. only admit students with a strong mathematics background to sciences, students with a sufficient language background to arts, etc. An alternative approach would be to consider the effect of an entry exam.

Table 5: Predictions and policy counterfactuals

	university	college	total
Observed choices and study outcomes (percentage)			
Enrollment	20.9	44.1	65.0
Success after 1 year	10.8	20.8	31.6
Diploma after 3 years	9.3	15.6	25.0
Diploma after 6 years	13.8	29.8	43.6
Predictions of dynamic model (percentage)			
Enrollment	26.2	38.9	65.1
Success after 1 year	11.9	18.5	30.4
Diploma after 3 years	8.9	13.3	22.2
Diploma after 6 years	14.4	22.3	36.7
Optimal uniform admission standard (percentage point change)[a]			
Enrollment	-6.5	+1.0	-5.5
Success after 1 year	-0.9	+2.0	+1.1
Diploma after 3 years	-0.1	+1.1	+1.0
Diploma after 6 years	-0.3	+1.7	+1.4
Optimal discriminatory admission standard, university programs only (percentage point change)[a]			
Enrollment	-10.0	+8.1	-1.9
Success after 1 year	-2.0	+4.6	+2.6
Diploma after 3 years	-0.5	+2.4	+1.9
Diploma after 6 years	-1.4	+3.7	+2.3

Note: Observed and predicted outcomes are expressed as percentages of 2001 high school graduates. Predicted outcomes of admission policies are expressed as percentage point changes relative to the status quo.

[a] "Optimal standard" refers to the threshold that maximizes the number of graduates in higher education after 6 years.

The first approach is consistent with admission policies in some countries, and it is feasible with our data. But it is inevitably somewhat ad hoc, since there are many possible selection criteria.[20] The second approach is a realistic description for several countries, but it cannot be directly implemented in our case, since entry exams did not take place. We

[20] We nevertheless implemented this approach. For example, we imposed admission criteria based on high-school background, where only pupils with a highschool background in mathematics, classical languages or sciences can start university, while all pupils can start college. We found that this policy has similar effects to an entry limited to university programs, which we discuss below.

therefore followed a variation of this second approach that mimics the effect of entry exams: we select students based on their first year success rates as predicted by the model. For example, we can introduce an admission standard in such a way that only pupils with a predicted success rate of at least 50% can start the program. More generally, we can vary the toughness of the admission standard by only allowing students to enter a program if they have a predicted success rate above an admission threshold of $X\%$. An admission threshold of 0% is the current status quo situation, where even students with 0% success rates are accepted. A positive but low admission threshold means a lax policy, while a high threshold means a strict policy and a threshold of 100% means that only students with guaranteed success are admitted. This approach incorporates in a systematic way all observed student characteristics that are relevant for success rates (in particular, high school background characteristics, which we found important predictors of success in the previous section) and also unobserved student characteristics captured by the different student types.

6.2 The impact of raising admission standards

Figure 2 shows the impact of uniform admission standards on educational attainment, as predicted by the model. We consider admission thresholds $X\%$ that are uniform across programs, and we vary the thresholds between 0% (the current situation) and 100% (no one is admitted). Figure 2 shows that the enrollment rate slowly decreases for low admission thresholds, and decreases faster for high thresholds. For example, raising the threshold from 0% to 20% reduces first-year participation from 65.1% to 62.1%, while raising the threshold further from 20% to 40% reduces first-year participation to 52.0% and raising the threshold from 40% to 60% further reduces enrollment to only 29.0%.

Despite the drop in initial enrollment, successful degree completion increases for low admission thresholds, and it only decreases mildly for intermediate thresholds. Only under sufficiently tight thresholds there is an important reduction in successful degree completion. For example, under the current 0% threshold 22.2% of high school students receive a degree after three years and 36.7% receive their degree after six years. An admission threshold of 20% *raises* these success rates to respectively 22.8% and 37.7%, and a tighter admission standard of 30% raises it further to 23.2% and 38.0%. However, a strict admission standard of 50% reduces degree completion to respectively 21.1% and 32.3%. In other words, introducing low or intermediate admission thresholds (below 40%) involves no main tradeoff from a policy perspective. On the one hand, it reduces first-year overall enrollment and hence requires lower educational resources. On the other hand, it also increases successful degree completion after 3 and 6 years, since it induces students to shift more quickly to programs according to their abilities. Tighter admission standards (above 40%) decrease enrollment further, but also lead to a decrease in degree completion.

Figure 2: Uniform admission standards

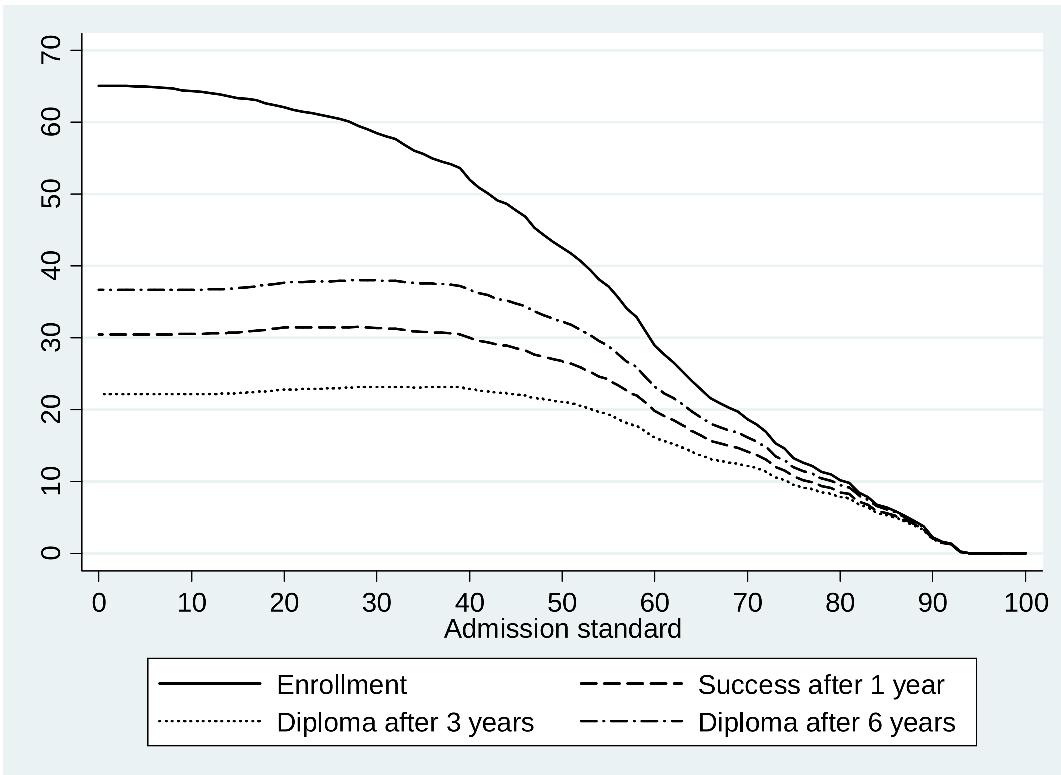


Figure A2 in Appendix 2 shows the impact on educational attainment of a similar experiment, i.e. discriminatory admission thresholds that only apply to university programs and not to college programs. This shows that admission thresholds limited to university programs only slightly decrease initial enrollment. But they raise overall degree completion after three and six years because of shifts from university to college programs, where the success rates are higher.

6.3 Optimal admission standards

To explore the shifts from university to college programs further, we now focus on "optimal" admission standards, i.e. admission thresholds that maximize the total number of graduates after 6 years (both for the uniform and discriminatory case). While this is not necessary an optimal policy in all respects, it reflects a broader policy objective to maximize attainment in higher education within a reasonable time frame. The uniform admission threshold that maximizes success after 6 years turns out to be 28% (the peak on the relevant line in Figure 2), while the discriminatory university admission threshold that maximizes success after 6 years is 42% (parallel peak in Figure A2).

Table 5 shows the results. The top two panels were discussed earlier and show the actual and predicted enrollment and completion rates. The third panel shows the changes in successful completion rates under a uniform admission threshold of 28%, and the bottom panel shows the changes in successful completion rates under a discriminatory admission policy of 42%.

Regarding the uniform admission threshold, we obtain the following findings. First-year participation sharply drops by 5.5% points (from 65.1% to 59.6%). The decrease only applies to universities (-6.5% points); there is even an increase in first-year participation at colleges (+1.0% points). This is because the admission threshold induces a shift from universities to colleges: intuitively, students with very low expected success rates at universities (below 28%) will now choose other programs at colleges where they have higher success rates. Furthermore, despite the sharp drop in first-year participation, the number of students who obtain a diploma increases, by 1.0% points after three years and by 1.4% points after six years. This increase can be fully attributed to colleges (+1.1% points after three years and +1.7% points after six years). At the same time, the drop in university diplomas is negligible (only -0.1% points after three years and -0.3% points after six years).

Regarding the discriminatory admission threshold to universities only, we obtain the following interesting additional findings. First-year participation also decreases, but by less than under a uniform threshold (-1.9% points instead of -5.5% points). At the same time, the number of successful students after three years and six years increases by more (+1.9% points and +2.3% points, compared with +1.0% points and +1.4% points under a uniform threshold). In other words, a discriminatory threshold that only limits access to universities implies lower savings in educational resources, but it also has a higher benefit in terms of eventual educational attainment. This conclusion is confirmed when we consider the shifts from universities to colleges: the discriminatory threshold implies a very sharp reduction of first-year university participation (-10.0% points versus -6.5% points under a uniform threshold), and an equally sharp shift to colleges (+8.1% points versus only +1.0% points under a uniform threshold). The consequence is a larger number of diplomas at colleges (+2.4% points after three years and +3.7% points after six years), but also a decline in the number of diplomas at universities (–0.5% points after three years and -1.4% points after six years).

The above discussion focused on how admission standards induce shifts from universities to colleges, raising student success rates. The admission standards also induce shifts within universities and within colleges to different majors. These are somewhat less pronounced, but they also help explaining how admission standards can raise the number of graduates.

To summarize, moderate admission thresholds can save on educational resources (in the sense of reducing unsuccessful participation), while at the same timing increasing overall educational attainment (both the speed and ultimate number of graduates after 6 years). A uniform admission standard has the largest resource savings, and turns out not to involve any tradeoffs, since it increases the number of college graduates without reducing the number of university graduates. A discriminatory admission standard has lower resource savings, but increases the number of graduates by even more. At the same time, however, a discriminatory admission standard involves some tradeoff: the number of college graduates sharply increases, at the expense of the number of university graduates, which slightly decreases.

7 Conclusion

We have studied how a higher education system without ex ante admission policies and only ex post student selection influences enrollment and completion. We developed a dynamic discrete choice model of college/university and major choice, where the outcome of the enrollment decision is uncertain. Upon observing past performance, students may decide to continue, reorient or drop out, thereby balancing their current costs and benefits against future expected benefits on the labor market. We accounted for the impact of a rich set of demographics and high school background characteristics on choices and study success, and we also controlled for unobserved heterogeneity influencing this process.

We applied our model to the region of Flanders, where there is essentially no ex ante screening and very strong ex post selection, especially after the first year. Success rates after the first year are low (less than 50%), but highly predictable by student characteristics (such as high school track record). Gender, high school background and distance to university/college play an important role in students' decisions of college/university and major. Furthermore, the dynamics show persistency in choices but also interesting switching behavior. Unsuccessful students mainly switch from university to college majors, or from college majors to drop-out. As a result, less than 40% of the students complete their first three years without delay and many need up to six years. This implies large losses from mismatching in the form of reorientation or drop-out.

We use the estimates to evaluate the effects of introducing ex ante admission policies. Our counterfactuals show that an ex ante screening system with modest admission thresholds can increase overall degree completion in higher education. First, we consider a uniform admission standard that applies to both colleges and universities. A modest admission threshold can reduce the first-year entry rate by 5.5% points, and at the same time increase overall educational attainment after six years by up to 1.4% points (+1.7% points at colleges and a negligible –0.3% points at universities). This is because the admission threshold induces a strong shift in the first year from universities to colleges, by students who would have had very low probability of success. Second, we consider a discriminatory admission standard which only applies to universities and not to colleges. A more restrictive admission threshold can reduce the first-year entry rate by –1.9% points, and raise educational attainment after six years by 2.3% points. However, this increase in educational attainment involves a large shift from universities to colleges: there is a large increase in college diplomas (+3.7% points), which comes at the expense of university diploma's (–1.4% points).

In sum, a suitably designed ex ante screening system can increase degree completion in higher education. A mild uniform admission standard turns out not to involve any trade-offs: it reduces the number of first-year entrants, and increases success rates and overall educational attainment after six years. A discriminatory admission standard to universities only can improve overall attainment by even more, but it involves trading off an increase in college graduates against a loss in university graduates.

The implied educational resource savings have a direct positive impact on government budgets. These savings can be used for general purposes, but also to make additional investments in the higher educational system, for example investments in the quality of education, or additional scholarships to groups from socially disadvantaged backgrounds. There are also indirect resource savings from faster educational attainment, as students enter more quickly on the labor market. In future research, it would be interesting to conduct a more complete welfare analysis, by matching our data on educational choices directly to data on labor market outcomes.

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Appendix 1: Details on the dynamic model

In this Appendix, we provide more details on how the expected value functions enter the choice probabilities. As discussed in the text, the probability that an individual chooses an option j in period t is given by:

$$\Pr(d_t^j = 1|\Phi_t, X_t) = \frac{\exp(V_t^j(\Phi_t, X_t))}{\sum_{j=0}^{J} \exp(V_t^j(\Phi_t, X_t))}, \tag{9}$$

where the conditional value function for a given option j is given by

$$V_t^j(\Phi_t, X_t) = u_t^j(\Phi_t, X_t) + \beta \left[\lambda_t^j \widetilde{V}_{t+1}(\Phi_{t+1}, X_t + 1) + (1 - \lambda_t^j) \widetilde{V}_{t+1}(\Phi_{t+1}, X_t) \right], \tag{10}$$

To compute the expected value functions $\widetilde{V}_{t+1}(\Phi_{t+1}, X_t + 1)$ and $\widetilde{V}_{t+1}(\Phi_{t+1}, X_t)$, there are two possible cases:

Case 1 *: No sufficient credits to graduate at the end of period t ($X_t < \overline{X} - 1$)*

If at time t a student has only accumulated $X_t < \overline{X} - 1$ credits, there is no chance she will graduate at the end of period t, so we can write:

$$\begin{aligned} \widetilde{V}_{t+1}(\Phi_{t+1}, X_t + 1) &= \gamma + V_{t+1}^0(\Phi_{t+1}, X_t + 1) - \log\left(\Pr(d_{t+1}^0 = 1|\Phi_{t+1}, X_t + 1)\right) && (11) \\ \widetilde{V}_{t+1}(\Phi_{t+1}, X_t) &= \gamma + V_{t+1}^0(\Phi_{t+1}, X_t) - \log\left(\Pr(d_{t+1}^0 = 1|\Phi_{t+1}, X_t)\right), && (12) \end{aligned}$$

and substitute these expressions into the condition value functions (10) entering the choice probabilities (9).

Case 2 *: Sufficient credits to graduate ($X_t = \overline{X} - 1$)*

If at time t a student has accumulated $X_t = \overline{X} - 1$ sufficient credits, there is a probability (λ_t^j) that she will graduate at the end of period t and enter the labor market with a diploma. In this case we can write:

$$\begin{aligned} \widetilde{V}_{t+1}(\Phi_{t+1}, X_t + 1) &= \alpha_5 \sum_{t=1}^{T} \beta^{t-1} w_t^j(S_0) && (13) \\ \widetilde{V}_{t+1}(\Phi_{t+1}, X_t) &= \gamma + V_{t+1}^0(\Phi_{t+1}, X_t) - \log\left(\Pr(d_{t+1}^0 = 1|\Phi_{t+1}, X_t)\right), && (14) \end{aligned}$$

and substitute these expressions into the condition value functions (10) entering the choice probabilities (9).

Appendix 2: Additional tables and figures

Enrollment and study outcomes

Table A1: Enrollment and success in higher education

		Enrollment			Success after 1 year			Diploma after 3 years			Diploma after 6 years		
	pupils	univ	coll	total	univ	coll	total	univ	coll	total	univ	coll	total
All pupils	55,524	20.9	44.1	65.0	10.8	20.8	31.6	9.3	15.6	25.0	13.8	29.8	43.6
Demographics													
Male	27,113	19.0	40.3	59.3	8.8	16.6	25.4	7.3	11.5	18.8	11.6	24.7	36.3
Female	28,411	22.8	47.7	70.4	12.7	24.7	37.4	11.3	19.6	30.9	15.8	34.7	50.6
On time	36,509	28.1	46.7	74.8	15.6	24.9	40.5	13.6	19.3	32.9	19.6	36.0	55.6
Repeated	19,015	7.3	39.0	46.3	1.5	12.8	14.4	1.1	8.7	9.8	2.5	17.9	20.4
High school program													
General HS	24,995	44.3	43.0	87.3	23.7	25.6	49.3	20.5	20.2	40.7	30.1	39.7	69.7
clas + math	3,331	74.7	15.4	90.1	48.6	9.9	58.5	42.7	7.6	50.3	59.7	20.0	79.7
clas + lang	2,373	61.9	27.3	89.2	33.5	16.7	50.3	30.1	12.8	42.9	43.2	30.3	73.5
sci + math	5,489	60.6	28.9	89.5	37.2	18.5	55.7	32.5	14.4	46.9	45.0	30.8	75.8
math + lang	2,717	40.0	46.6	86.6	17.9	29.7	47.5	15.1	23.3	38.4	24.5	45.7	70.3
econ + math	2,556	38.9	49.6	88.6	19.1	32.6	51.8	16.0	26.6	42.6	23.9	47.9	71.8
econ + lang	5,273	20.3	65.3	85.7	6.4	36.8	43.1	5.2	29.5	34.6	9.5	54.7	64.2
human	3,256	19.9	62.0	82.0	4.6	33.0	37.7	3.5	25.6	29.1	7.6	45.6	53.3
Technical HS	19,961	2.2	59.0	61.2	0.3	23.1	23.4	0.2	16.6	16.9	0.5	30.4	31.0
management	5,490	3.0	67.8	70.8	0.3	25.6	25.8	0.2	19.1	19.4	0.5	36.5	37.0
sci + tech	2,616	5.7	70.5	76.2	1.3	32.8	34.1	0.9	22.0	22.9	2.0	44.0	46.0
social + tech	2,320	0.6	77.9	78.6	0.0	29.8	29.8	0.0	22.6	22.7	0.1	41.1	41.2
technics	5,297	0.5	41.7	42.2	0.1	16.8	16.9	0.1	11.4	11.5	0.2	18.4	18.6
other tech	4,238	2.3	51.7	54.0	0.2	18.0	18.2	0.1	13.3	13.4	0.3	23.4	23.7
Artistic HS	1,203	6.3	61.1	67.4	1.1	27.6	28.7	1.0	16.2	17.2	2.2	30.1	32.3
Vocational HS	9,365	0.2	12.9	13.2	0.0	2.0	2.0	0.0	1.3	1.3	0.0	2.2	2.2
Observations	55524	11,631	24,473	36,104	5,992	11,527	17,519	5,187	8,677	13,864	7,645	16,554	24,199

Note: Percentage of high school graduates who choose for each option, based on own calculations

Table A2: Reorienation of failed first year students

Choice in period 1	Choice in period 2										
	University					College					Total
	SCI	BIOM	SSCI	ARTS	Total	SCI	BIOM	SSCI	ARTS	Total	
University											
SCI	54.8	2.8	4.9	1.3	63.8	15.2	1.7	15.2	0.6	32.7	96.5
BIOM	3.5	53.3	5.2	2.5	64.5	6.1	13.2	12.5	0.8	32.6	97.1
SSCI	0.2	1.0	57.0	2.3	60.5	2.1	1.8	29.4	1.7	35.0	95.5
ARTS	0.2	0.3	5.1	53.9	59.5	1.9	1.0	24.8	5.8	33.5	93.0
College											
SCI	0.2	0.6	1.6	0.6	3.0	49.8	2.3	14.4	0.9	67.4	70.4
BIOM	0.2	0.3	0.3	0.3	1.1	2.2	44.9	19.6	0.5	67.2	68.3
SSCI	0.1	0.1	0.8	0.3	1.3	2.5	2.0	58.4	0.9	63.8	65.1
ARTS	0.0	0.4	3.0	2.2	5.6	4.2	1.3	29.5	40.0	75.0	80.6

Note: The columns represent the proportion of failed students who choose for each option in period 2 given their choice in period 1.

Wages

Table A3: Determinants of log wages

Variables	Coefficient	St. error
majors		
SCIuniv	0.333*	(0.037)
BIOMuniv	0.371*	(0.072)
SSCIuniv	0.274*	(0.028)
ARTSuniv	0.177*	(0.042)
SCIcoll	0.172*	(0.037)
BIOMcoll	0.080	(0.107)
SSCIcoll	0.160*	(0.029)
ARTScoll	0.179*	(0.066)
gender		
male	0.191*	(0.005)
SCIuniv	-0.059*	(0.014)
BIOMuniv	-0.098*	(0.025)
SSCIuniv	-0.039*	(0.010)
ARTSuniv	-0.111*	(0.020)
SCIcoll	-0.061*	(0.011)
BIOMcoll	-0.057*	(0.020)
SSCIcoll	-0.031*	(0.008)
ARTScoll	-0.085*	(0.031)
experience		
years of experience	0.013*	(0.000)
SCIuniv	0.022*	(0.001)
BIOMuniv	0.015*	(0.001)
SSCIuniv	0.023*	(0.001)
ARTSuniv	0.014*	(0.001)
SCIcoll	0.014*	(0.000)
BIOMcoll	0.006*	(0.001)
SSCIcoll	0.009*	(0.000)
ARTScoll	0.008*	(0.002)
constant	9.952*	(0.021)

Note: Number of observations: 37,434 workers

* statistical significance at 5% level.

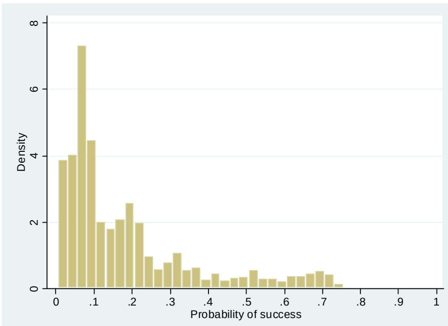
Interaction effects between majors and region dummies are also included.

Success probabilities

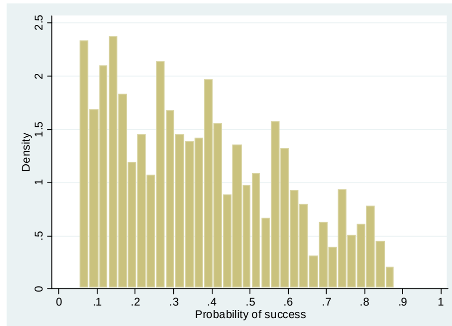
Figure A1: Predicted first-year success probabilities

SCI

univ

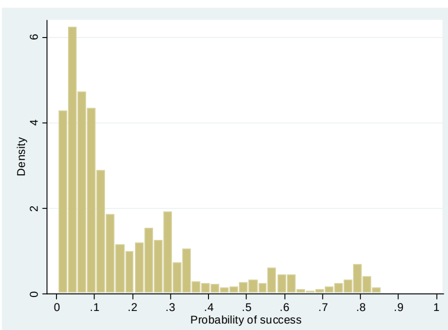


coll

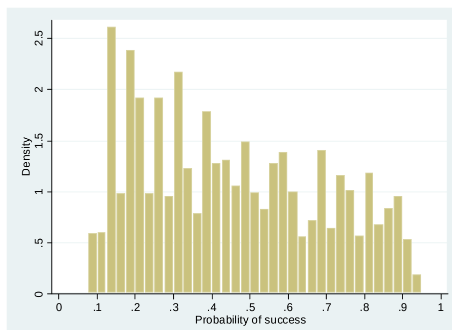


BIOM

univ

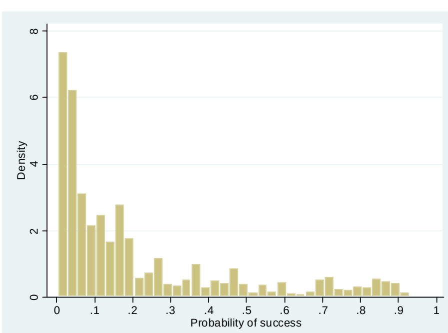


coll

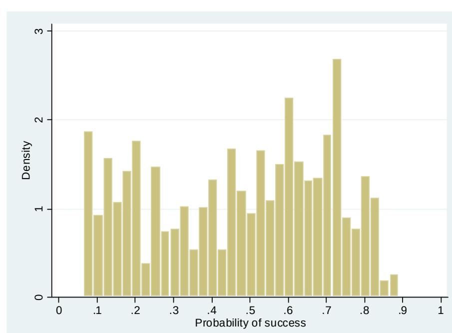


SSCI

univ

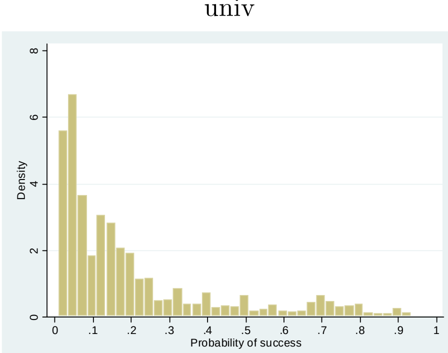


coll



ARTS

univ



coll

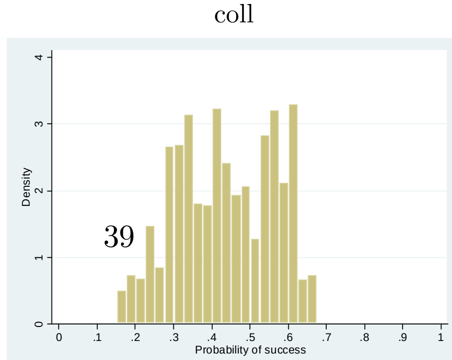


Table A4: The probability of success

Period	credits	Coefficient	St. error
period 2	0	0.466*	(0.028)
	1	1.844*	(0.034)
period 3	0	0.325*	(0.051)
	1	1.425*	(0.038)
	2	3.200*	(0.062)
period 4	0	0.038	(0.111)
	1	1.016*	(0.056)
	2	2.445*	(0.056)
period 5	0	-1.435*	(0.267)
	1	-0.214*	(0.092)
	2	1.405*	(0.064)
period 6	0	-1.351*	(0.360)
	1	-0.314*	(0.139)
	2	0.718*	(0.103)

Note: Sample of 60% of 55,524 high school graduates, up to 6 periods

Base category = 0 credits in period 1

Table A4: The probability of success (continued)

	SCI UNIV		BIOM UNIV		SSCI UNIV		ARTS UNIV	
	Coef.	St. error	Coef.	St. error	Coef.	St. error	Coef.	St. error
constant type 1	-0.589*	(0.232)	-0.929*	(0.257)	-1.486*	(0.166)	-0.851*	(0.194)
constant type 2	-3.092*	(0.257)	-3.472*	(0.279)	-3.928*	(0.185)	-3.870*	(0.250)
male	-0.254*	(0.107)	-0.213*	(0.099)	-0.488*	(0.057)	-0.415*	(0.105)
general HS[a]								
clas + math	1.750*	(0.229)	2.474*	(0.260)	3.658*	(0.182)	3.670*	(0.250)
clas + lang	1.053*	(0.722)	0.923*	(0.322)	2.496*	(0.176)	2.197*	(0.197)
sci + math	1.550*	(0.214)	2.275*	(0.247)	3.375*	(0.181)	2.235*	(0.270)
math + lang	0.606*	(0.262)	1.130*	(0.276)	1.929*	(0.176)	1.577*	(0.223)
econ + math	0.140	(0.305)	0.945*	(0.330)	1.875*	(0.170)	1.397*	(0.374)
econ + lang	-0.745*	(0.660)	-0.338	(0.443)	0.911*	(0.165)	0.679*	(0.199)
human	-0.816*	(0.746)	-0.491	(0.578)	0.862*	(0.175)	0.560*	(0.210)
repeated	-0.750*	(0.200)	-0.916*	(0.172)	-0.873*	(0.081)	-0.655*	(0.145)
catholic HS	0.117	(0.116)	0.329*	(0.126)	0.459*	(0.072)	0.150	(0.130)

Note: Sample of 60% of 55,524 high school graduates, up to 6 periods

* statistical significance at 5% level

[a] Base category = technical, artistic or professional high school

Table A4: The probability of success (continued)

	SCI COLL		BIOM COLL		SSCI COLL		ARTS COLL	
	Coef.	St. error	Coef.	St. error	Coef.	St. error	Coef.	St. error
constant type 1	-1.114*	(0.230)	-0.387	(0.266)	-1.084*	(0.082)	-0.300	(0.301)
constant type 2	-2.363*	(0.244)	-1.555*	(0.285)	-1.712*	(0.085)	-0.283	(0.321)
male	-0.258*	(0.072)	-0.384*	(0.090)	-0.588*	(0.031)	-0.163*	(0.103)
general HS[b]								
clas + math	2.554*	(0.260)	2.376*	(0.342)	2.797*	(0.139)	0.493	(0.382)
clas + lang	2.138*	(0.380)	1.533*	(0.338)	2.263*	(0.113)	0.537	(0.331)
sci + math	2.685*	(0.243)	2.624*	(0.305)	2.429*	(0.106)	0.381	(0.374)
math + lang	1.915*	(0.253)	1.930*	(0.305)	2.385*	(0.105)	0.504	(0.336)
econ + math	1.903*	(0.256)	1.618*	(0.326)	2.308*	(0.098)	0.754	(0.446)
econ + lang	1.345*	(0.260)	0.896*	(0.283)	1.881*	(0.084)	-0.304	(0.305)
human	1.181*	(0.273)	0.699*	(0.275)	1.810*	(0.089)	0.227	(0.318)
technical HS[b]								
management	0.770*	(0.255)	0.065	(0.286)	1.213*	(0.081)	-0.584	(0.347)
sci + tech	1.433*	(0.229)	0.670*	(0.275)	1.324*	(0.100)	0.519	(0.486)
social + tech	1.169*	(0.296)	0.397	(0.270)	1.027*	(0.091)	-0.239	(0.443)
technics	1.346*	(0.227)	0.700*	(0.302)	0.916*	(0.121)	0.037	(0.435)
other tech	1.012*	(0.285)	0.378	(0.268)	1.051*	(0.088)	-0.670	(0.451)
artistic HS[b]	1.068*	(0.258)	0.910	(0.578)	0.882*	(0.147)	0.265	(0.295)
repeated	-0.669*	(0.058)	-0.706*	(0.087)	-0.523*	(0.032)	-0.660*	(0.117)
catholic HS	0.269*	(0.066)	0.383*	(0.102)	0.269*	(0.036)	0.257*	(0.115)

Note: Sample of 60% of 55,524 high school graduates, up to 6 periods

* statistical significance at 5% level.

[b] Base category = vocational secondary education

Dynamic discrete choice model

Table A5: Dynamic discrete choice model

Variables		Coef.	St. error
Utility parameters			
travel costs (α_2)		-0.298*	(0.003)
credits (α_3)		1.955*	(0.024)
earnings (α_5)		0.005*	(0.000)
Switching costs			
d_t^j	d_{t-1}^j		
SCI	BIOM	-4.238*	(0.096)
	SSCI	-4.253*	(0.073)
	ARTS	-4.626*	(0.139)
BIOM	SCI	-3.075*	(0.086)
	SSCI	-3.750*	(0.069)
	ARTS	-5.217*	(0.213)
SSCI	SCI	-2.558*	(0.050)
	BIOM	-3.371*	(0.050)
	ARTS	-2.859*	(0.054)
ARTS	SCI	-3.147*	(0.127)
	BIOM	-4.434*	(0.189)
	SSCI	-3.460*	(0.077)
UNIV	COLL	-5.436*	(0.072)
COLL	UNIV	-0.470*	(0.034)
type 1		39.3%	
type 2		60.7%	
β		0.95	(0)

Note: Sample of 60% of 55,524 high school graduates,
24 choice alternatives, up to 6 periods
* statistical significance at 5% level
^{c} Base category = same option in the previous period

Table A5: Dynamic discrete choice model (continued)

	SCI UNIV[a]		BIOM UNIV[a]		SSCI UNIV[a]		ARTS UNIV[a]	
	Coef.	St. error	Coef.	St. error	Coef.	St. error	Coef.	St. error
constant type 1	-4.820*	(0.104)	-4.362*	(0.111)	-3.283*	(0.072)	-3.431*	(0.085)
constant type 2	-9.854*	(0.130)	-9.175*	(0.131)	-6.872*	(0.086)	-7.774*	(0.112)
male	1.064*	(0.066)	-0.435*	(0.061)	-0.051	(0.044)	-0.017	(0.060)
general HS[a]								
clas + math	7.519*	(0.135)	7.365*	(0.144)	5.594*	(0.110)	5.674*	(0.128)
clas + lang	4.185*	(0.294)	5.921*	(0.182)	5.676*	(0.113)	6.269*	(0.127)
sci + math	5.627*	(0.150)	7.398*	(0.131)	5.044*	(0.098)	4.844*	(0.131)
math + lang	1.939*	(0.259)	5.680*	(0.152)	4.893*	(0.108)	4.803*	(0.130)
econ + math	4.557*	(0.166)	4.174*	(0.175)	4.515*	(0.106)	2.806*	(0.179)
econ + lang	1.939*	(0.257)	2.532*	(0.199)	3.343*	(0.086)	2.888*	(0.108)
human	2.315*	(0.305)	2.610*	(0.241)	3.319*	(0.095)	3.097*	(0.118)
repeated	-1.165*	(0.098)	-0.571*	(0.093)	-0.497*	(0.054)	-0.666*	(0.078)

Note: Sample of 60% of 55,524 high school graduates, 24 choice alternatives, up to 6 periods

[a] Base category = drop-out option

[b] Base category = technical, artistic or vocational high school

Table A5: Dynamic discrete choice model (continued)

	SCI COLL[a]		BIOM COLL[a]		SSCI COLL[a]		ARTS COLL[a]	
	Coef.	St. error	Coef.	St. error	Coef.	St. error	Coef.	St. error
constant type 1	-3.718*	(0.101)	-3.593*	(0.121)	-1.949*	(0.047)	-4.492*	(0.135)
constant type 2	-5.750*	(0.107)	-6.060*	(0.129)	-2.912*	(0.045)	-6.411*	(0.143)
male	0.724*	(0.046)	-0.864*	(0.052)	0.000	(0.028)	-0.229*	(0.058)
general HS[b]								
clas + math	3.347*	(0.135)	3.989*	(0.164)	0.425*	(0.090)	3.810*	(0.186)
clas + lang	2.306*	(0.186)	4.009*	(0.175)	1.070*	(0.087)	0.186*	(0.166)
sci + math	3.852*	(0.116)	4.098*	(0.145)	0.742*	(0.071)	3.440*	(0.180)
math + lang	3.514*	(0.130)	4.083*	(0.152)	1.162*	(0.077)	4.161*	(0.166)
econ + math	2.947*	(0.132)	3.384*	(0.163)	1.290*	(0.076)	2.651*	(0.202)
econ + lang	1.910*	(0.124)	2.874*	(0.141)	1.501*	(0.057)	3.495*	(0.149)
human	2.185*	(0.134)	3.500*	(0.142)	1.386*	(0.061)	3.074*	(0.157)
technical HS[b]								
management	1.375*	(0.118)	2.228*	(0.141)	1.403*	(0.049)	2.045*	(0.164)
sci + tech	2.419*	(0.109)	2.768*	(0.140)	0.662*	(0.064)	0.904*	(0.217)
social + tech	1.791*	(0.143)	3.636*	(0.139)	1.687*	(0.063)	2.020*	(0.214)
technics	2.230*	(0.104)	1.955*	(0.148)	-0.070*	(0.068)	0.912*	(0.203)
other tech	0.787*	(0.132)	2.517*	(0.132)	0.934*	(0.053)	1.336*	(0.204)
artistic HS[b]	2.061*	(0.135)	0.498*	(0.250)	0.239*	(0.093)	3.507*	(0.149)
repeated	-0.353*	(0.043)	-0.416*	(0.053)	-0.184*	(0.028)	-0.092*	(0.065)

Note: Sample of 60% of 55,524 high school graduates, 24 choice alternatives, up to 6 periods

[a] Base category = drop-out option

[b] Base category = vocational secondary education

Policy counterfactuals

Figure A2: Admission standards limited to programs at university