Enrollment and degree completion in higher education without admission standards

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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 of 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 to evaluate the effects of alternative, ex ante admission policies. We find that well-designed moderate admission standards reduce unsuccessful initial enrolment and at the same time do not decrease degree completion. This is because ex ante screening better matches students to the right majors, reducing the probability of early drop-out.

JEL codes: I21, I23, I28

Keywords: Dynamic discrete choice, Higher education, Admission policies

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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, 2016) illustrates the problems in the organization of higher education: up to 59% of today's young adults in OECD countries enter a university-level program, but only 36% are expected to complete it. Among the students who complete a degree, a large fraction incurs substantial delays.

Several countries have used ex ante screening policies to influence the possible tradeoffs between enrollment and degree completion. Ex ante screening may take place through entry exams or admission standards based on high school performance. In the U.S., there is ex ante screening through admission standards, though this mainly applies to universities and not to the community colleges. In Europe, countries follow more diverse admission policies. Some countries have also relied upon ex ante admission policies, most notably in the U.K., Ireland and the Scandinavian countries. In contrast, some other European countries largely select students on an ex post basis: admission standards (and tuition fees) are very low, and students are selected based on their performance during their higher education.[1] Institutions can do such an ex post selection because they have autonomy in giving credits based on student performance during 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 to other majors. This system of ex post selection leads to large costs, both the direct costs of higher education and indirect costs stemming from foregone earnings in the labor market.

The main contribution of this paper is to analyze such an ex post selection system and to assess how a move towards ex ante screening would affect initial enrollment and degree completion. Our main finding is that the introduction of well-designed modest admission standards would reduce unsuccessful initial enrollment without lowering degree completion.

[1] Some of the countries that select students on an ex post basis also set low ex ante admission standards (in the form of high school degree requirements), while other countries do not set any ex ante admission standards.

This is because ex ante screening better and more quickly matches students to the right majors. This reduces the probability of early drop-out and increases the probability that enrolled students complete their degree.

To establish our findings, 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, and also control 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 most preferred 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).

We find that success rates after the first year are low (less than 50%), but highly predictable by student characteristics (such as high school track record). Regarding study choices, we find that students are responsive to distance to universities and colleges and expected future earnings. Furthermore, we find that 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. Intuitively, students tend to enroll in programs with a low probability of graduating because they value the higher labor market returns associated with more difficult programs, while they bear only a limited part of the costs as higher education is highly subsidized.

We proceed by assessing how the dynamic model predicts observed first-year enrollment and study outcomes. We show that the model performs reasonably well both within the estimation sample and also out-of-sample. We then 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. We consider the effects of such admission policies on both overall degree completion (the number of students that eventually graduate) and on the relative number of students that graduate without delay. We distinguish between the impact of uniform and discriminatory admission thresholds.

First, we consider a uniform admission standard that applies to both college and university majors. We find that modest uniform admission standards decrease enrollment without lowering degree completion. More specifically, an admission threshold to students with a predicted success rate of at least 20% reduces the first-year entry rate by 8.4% points, but at the same time does not decrease overal educational attainment. The fraction of students graduating within the minimal required time even increases by 0.5% points. Intuitively, this is because the admission standard induces a shift from universities to colleges in the first year by students with very low success rates at universities. The admission standard also induces shifts within universities and colleges to programs that better match students' abilities. As a result more students pass the first year, and fewer students end up dropping out without a degree. Stricter admission standards further reduce first-year enrollment, but would also imply a reduction in final degree completion. For example, a stricter admission standard of 40% further decreases enrollment by 14.5% points, but also reduces educational attainment by 1.2% points. The admission policy based on "predicted success rates" aims to mimic admission standards that are based on intrinsic skills required to perform well in higher education. This would in particular apply to entry exams: these are typically designed to select those students that are most likely to perform well at the intended study program.

Second, we consider a discriminatory admission standard which applies only 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] The 20% and 40% admission thresholds limited to university programs have a smaller impact on total enrollment of respectively -0.4% points and -0.6% points, but lead to a higher number of graduates (+0.5% points and +1.1% point). However, this increase in educational attainment also involves a shift from universities to colleges: the 40% discriminatory threshold leads to an increase in college diplomas (+3.6% points), which comes at the expense of university diplomas (-2.5% points). This shift may not be desirable as the wage gap between university and college degrees is large.

In sum, well-designed moderate uniform admission standards reduce (unsuccessful) enrollment in the first year, while overall educational attainment does not decrease. Discriminatory standards can have a larger positive impact on degree completion, but involve trading off university versus college attainment. However, the total welfare effect of introducing moderate uniform admission standards may not necessarily be positive. In a system with ex ante

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

admission standards, some students will no longer have the option to enroll in higher education or to start at their most preferred study program, which decreases their utility. Stange (2012) shows that students may learn about their ability during college. Students obtain an option value from attending college and dropping out after a bad performance.

Our research relates to several strands of literature. There is a quite extensive literature on ex ante screening systems of higher education, 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), Stange (2012), Fu (2014), and Arcidiacono et al. (2016). Closest to our research is a recent paper by Bordon and Fu (2015). They use a structural approach to analyze the college-major specific admission system in higher education in Chile. They conclude that switching from admission on the basis of college and major to admission only on the basis of college, would improve students' welfare. While that paper focuses on a shift *within* an ex ante screening system, our paper focuses on a shift from an ex post selection to an ex ante screening system, to show how this can reduce study duration without inducing drop-out.

There has been only very limited research on ex post selection systems in various European countries. A small literature analyses how financial incentives can influence study duration or time to complete a degree, see for example Garibaldi et al. (2012) and Gunnes et al. (2013).[3] Our paper does not consider financial incentives *within* an ex post system, but instead considers how the introduction of ex ante admission standards can improve outcomes. By simulating the impact of ex ante admission standards, we can thus compare the effectiveness of both systems.

Finally, from a methodological perspective, our paper relates to the dynamic discrete choice literature which analyzes 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.[4] See in particular Keane and Wolpin (1997), Arcidiacono (2004 and 2005), Joensen and Mattana (2017), Johnson (2013) and Bordon and Fu (2015). Contrary to previous studies of countries with ex ante admission policies, the unique setting of ex post selection in our paper allows us to observe the preferred option of students since choices are hardly constrained.

[3] Garibaldi, Giavazzi, Ichino and Rettore (2012) show how an increase in continuation tuition at Bocconi university reduces the probability of late graduation, without inducing more drop-outs. Gunnes, Kirkeboen and Ronning (2013) show how a restitution in Norway to students who complete their program on time reduced study delay. Other studies on financial incentives and time to complete a degree include Hakkinen and Uusitalo (2003), Heineck, Kifman and Lorenz (2006), and Dynarski (2003).

[4] Earlier static discrete choice models consider the first year decision of major and institution choice, and analyze the effect of travel costs and tuition fees on enrollment, e.g. Long (2004), Frenette (2006) and Kelchtermans and Verboven (2010).

Furthermore, we consider much richer choice sets than in current dynamic discrete choice models, and we incorporate both observed and unobserved heterogeneity in educational choices and study outcomes.

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. Section 5 discusses the empirical results and assesses model predictions. Finally, 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 (2014) 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. Arcidiacono et al. (2016) show that college completion rates would be higher if students would have perfect information on their ability. 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 (2008) 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 ex post selection. Countries also differ in the level of tuition fees.

We can classify countries in two groups. A first group mainly selects students ex ante, through both screening policies and tuition fees. An example is the U.S., where institutions set their own admission standards within boundaries set by the states (Cremonini et al., 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.[5] 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.[6]

Some European countries in this first group have low tuition fees, but still screen 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).[7] 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 (Cremonini et al., 2011). In Finland (Cremonini et al., 2011) universities select students through entry examinations, and governments restrict entry through a numerus clausus in all programs. In Denmark (Cremonini et al., 2011), admissions are based on grades in high school. The Danish government also determines the maximum number of students in specific fields of study.

A second 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, Switzerland and Austria, all high school graduates who passed a national exam are eligible to start at most programs at public universities.[8] In the Netherlands, students with an appropriate high school degree

[5]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 (Cremonini et al., 2011).

[6]As discussed in Cremonini et al. (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).

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

[8]In Italy, students have to pass an entry exam only for programs for which the Italian law imposes a maximum number of students (Merlino and Nicolo, 2012). Private institutions can set their own admission

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.[9] In Belgium, the focus of our analysis, all high school graduates are allowed to start at almost all programs in higher education.

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.[10] 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 (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. Institutions are not allowed to set their own admission standards.[11] Tuition fees are also low, currently capped at 890 EUR in Flanders and 837 EUR in the French-speaking community.

Two types of institutions offer higher education programs in Flanders: universities and colleges.[12] 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

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standards. In Switzerland, all study programs that do not have capacity restrictions are open to students who passed the Swiss Matura (Cremonini et al., 2011). In Austria, pupils who pass the secondary leaving examinations, typically can enroll in university studies of their choice (Helms, 2008).

[9] 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.

[10] 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)

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

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

the region. They have a large size, do not specialize in specific programs but 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. All universities and colleges receive public funding on the basis of enrolled students. There are also no capacity constraints and quality is regulated with uniform standards across the entire region. This makes distance the most important factor for students in deciding at which institution to enroll.

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 during higher education. 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 during a period of six years with information on their performance. As in Kelchtermans and Verboven (2010), we combine both datasets so that we can identify which students start with higher education and which students immediately start working after completing high school. We consider only students who enroll in higher education immediately after secondary school graduation. In Flanders, it is not common to delay enrollment after high school. Kelchtermans and Verboven (2010) document that only 2% of high school graduates enrolled with one year of delay.

In the combined dataset, we observe various personal characteristics, including gender, age, 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). Our measure of time-to-degree is time to complete the first 3 years, which amounts to completing a bachelor degree.[13] 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. In our dataset, we can follow students during 6 years in higher education. We thus observe whether students complete their bachelor degree within 3 years, 4 years, 5 years or 6 years (or whether they drop out during these years).[14]

First-year enrollment and subsequent success Table 1 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 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, 43.6% of the high school graduates have obtained their diploma, which is about 67% of the participating students.

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 degree 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

[13] The year 2001 was before the actual bachelor-master reform, but the total length of study remained the same after the reform. The bachelor-master reform increased the flexibility in higher education. For example, students no longer have to pass all courses in a given year to start courses in the next year of the program.

[14] A small fraction of students (2.1%) are still in our dataset after 6 years without having obtained a degree. We assume that they drop out of education after period 6.

also considerably more likely to obtain their diploma within the required three years or after six years.

Table 1: 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	46.8
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 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 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. Aucejo and James (2017) find a similar pattern in educational attainment between men and women, and Autor et al (2016) find a similar gender gap in high school completion for the U.S. 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 2 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. This corresponds to 43.6% of high school graduates in Table 1 (because only 65.0% of high school students start 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 for 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 Stinebrickner (2014).[15] Table A2 in Appendix 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 2: 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

[15] 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). 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 $t = 1, \dots, T$, students choose one of the available alternatives $j = 0, \dots, J$. A study option $j = 1, \dots, J$ refers to one of the four possible majors (SCI, BIOM, SSCI or ARTS) at five possible university campuses or at the nearest college. The option $j = 0$ refers to the decision to drop out and enter the labor market.[16] Modelling the major and college/university choice turns out to be important in our setting as the impact of high school background on choices and success differs between these options. In the counterfactual analysis, we also consider admission standards that are specific to each option. Travel distance is another important determinant of study choices. Kelchtermans and Verboven (2010) show for the region of Flanders that travel distance has a small effect on the participation decision, but a strong impact on the decision where and what to study. Considering distance is important in our setting as study decisions might be different depending on the program supply in the neighborhood of the student. For example, a student living in a neighborhood with college campuses, but no university campus, will be more likely to choose for a college program than a student living in an area with access to both college and university programs. Distance can also affect the results of our counterfactual analysis as restricting

[16] University campuses are located in Antwerp, Brussels, Ghent, Hasselt and Leuven. Since one of the five universities university campuses does not offer ARTS as a major, the total number of options is 24 (1 drop-out option, 19 options at universities, and 4 options at colleges).

the choice set of students might result in different choices depending on the program supply in the students' neighborhood.

To facilitate the computation of the model, we model the choice between the several university campuses but not between the several college locations. When students go to college, they are assumed to go to the nearest college campus where the major is available. Students who enroll at a university program travel on average 45.2km. Due to the broader geographic coverage of college campuses, travel distance is lower for college students, only 30.9km.

Students have to accumulate three credits (=years of coursework) to obtain their diploma, which corresponds to three years of successful studying. We allow for both uncertainty in obtaining a degree and also in the time to obtain a degree. Credit accumulation 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 successful, 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. Similar to Bordon and Fu (2015), we assume that wages depend on students' characteristics and the obtained diploma, and are independent of the time spent in higher education. This implies that attending college or university without obtaining a degree does not lead to higher wages relative to high school graduates. The open access policy in Flanders, combined with the very low credit accumulation of dropouts, make this a reasonable assumption.

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.

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 successfully 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.

In contrast to Arcidiacono (2004), Stange (2012), and Arcidiacono et al (2016), students do not update their ability through learning. Students update their choices conditional upon the state, which is determined by both observed and unobserved preference and performance shocks. Our model has the property that students are less likely to enroll when they are unlikely to succeed, because they account for the probability of success given their discount factor. Nevertheless, because there is heterogeneity in preferences for different study programs, there are still (small) fractions of students who enroll in programs where they have a low success probability. In our model, students may decide to enroll in such programs because they value the higher labor market returns associated with more difficult programs. In practice, students may also enroll in programs with a low success probability for reasons outside our model, for example when they have imperfect information about their success rates. In a model that allows for learning about ability, Arcidiacono et al. (2016) show that providing better information about expected success rates to students would also increase degree completion.

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.[17] 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

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

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.[18] 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. Similar to Arcidiacono et al. (2016), a student's utility 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. Finally, utility

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

[18] We do not observe whether students commute or go on residence. We can expect that distance is less important for students who live further and decide to go on residence. We obtained similar results when we included a quadratic effect of distance in the model.

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 alternative specific preference shocks capture the fact that new information about alternative specific tastes is revealed.

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 $u_t^0(S_0) = \alpha_5 w_t^0(S_0) + \varepsilon_t^0$.

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 successful and $X_{t+1} = X_t$ if she fails. The probability of success is $\lambda_t^j(S_0, X_t, t, \eta_t^j)$, 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. Finally, success depends on an error term η_t^j, which is i.i.d. across individuals and options. Students can perform better or worse than expected at the start of the period.

If students have accumulated $\overline{X}$ credits, they enter the labor market and earn wages $w^j(S_0)$ 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 $w^0(S_0)$. In our application, we consider $\overline{X} = 3$, so we assume a diploma is obtained after the first three years.[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 known only 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

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

[19] This corresponds to the bachelor diploma. In practice, bachelor university programs are followed by a 1- or 2-year master program. Incorporating this would have only a limited impact on the analysis, because almost all bachelor university students subsequently enroll at the corresponding master program and a large portion completes the program without further delay.

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 successful 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. 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 requires only 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 depends only 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.

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

$$\widetilde{V}_{t+1}(\Phi_{t+1}, X_t + 1) = \gamma + V^0_{t+1}(\Phi_{t+1}, X_t + 1) - \log\left(\Pr(d^0_{t+1} = 1|\Phi_{t+1}, X_t + 1)\right) \quad (7)$$

$$\widetilde{V}_{t+1}(\Phi_{t+1}, X_t) = \gamma + V^0_{t+1}(\Phi_{t+1}, X_t) - \log\left(\Pr(d^0_{t+1} = 1|\Phi_{t+1}, X_t)\right), \quad (8)$$

and substitute these expressions into the conditional value functions (2) entering the choice probabilities (5).

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^j_t) that she will graduate at the end of period t and enter the labor market with a diploma. In this case we can write:

$$\widetilde{V}_{t+1}(\Phi_{t+1}, X_t + 1) = \alpha_5 \sum_{t=1}^{T} \beta^{t-1} w^j_t(S_0) \quad (9)$$

$$\widetilde{V}_{t+1}(\Phi_{t+1}, X_t) = \gamma + V^0_{t+1}(\Phi_{t+1}, X_t) - \log\left(\Pr(d^0_{t+1} = 1|\Phi_{t+1}, X_t)\right), \quad (10)$$

and substitute these expressions into the condition value functions (2) entering the choice probabilities (5).

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 (11) is given by:

$$\ln L(\alpha, \theta) = \sum_{i=1}^{N} \sum_{t=1}^{T} \left(\ln L_{1it}(\alpha) + \ln L_{2it}(\theta)\right), \tag{11}$$

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 make use of a large survey dataset, "Vacature salarisenquete", containing information for 37,434 workers in Flanders in 2006. Second, we predict the success probabilities for each student in each possible state based on a flexible binary logit specification. We include gender and a large set of high school background variables, interacted with the 4 majors at colleges and universities. 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. 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. These unobserved characteristics may also be related to high school background. For example, students with a high unobserved ability during college might also be more likely to have graduated from more difficult high school programs. To account for this initial conditions problem, we do not restrict unobserved types to be orthogonal to observed student characteristics, but we allow for correlation between both by conditioning unobserved types upon high school background.[20] In our model, we do not allow for unobserved heterogeneity in

[20] We also estimated a model where we imposed that unobserved characteristics are orthogonal to high school background. Accounting for the potential initial conditions problem affects the size of the parameter

wages because we predict wages from a separate dataset. Our model does therefore not allow for the fact that individuals with unobserved high success rates in higher education might also have a higher unobserved labor market productivity.

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 $\pi_m(S_0)$ be the probability of belonging to type m, conditional upon observed (initial) student characteristics S_0. 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 (12):

$$\ln L(\alpha, \theta) = \sum_{i=1}^{N} \ln \left(\sum_{m=1}^{M} \left(\pi_m(S_0) \prod_{t=1}^{T} \left(L_{1imt}(\alpha) \times L_{2imt}(\theta) \right) \right) \right) \tag{12}$$

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 that an individual belongs to type m, and we maximize the log likelihood of success and the log likelihood of the choice model with respect to the parameters θ and α respectively. In the second step, we update the probability that individual i belongs to type m, using the EM algorithm. We repeat this procedure until convergence.[21] We estimate the standard errors using a bootstrap procedure with 500 replications. Our main specification considers $M = 2$ different types. We also estimated a model with 3 types. These results are similar but the type coefficients are slightly more difficult to interpret.

To estimate the model, we have a very large number of observations: 55,524 high school pupils who can choose between 24 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 estimate the model, we randomly sample 70% of the pupils. We use the remaining 30% of the pupils to validate our model.

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

estimates, but does not affect the main conclusions in our counterfactual analysis.

[21] See for example Arcidiacono and Ellickson (2011) for a detailed description of the EM algorithm estimation procedure in dynamic discrete choice models.

in the second part of this section. Finally, we assess how the model predicts the observed outcomes in the data.

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 the expected future wages under alternative diplomas, we assume that students expect their wages to be the same as the wages of workers with similar characteristics. We follow Johnson (2013) and Bordon and Fu (2015), and use a separate wage dataset to predict the expected wages for students. Students then take into account these expected wages in their educational decisions. Note that some studies include wages by explicitly modeling labor market decisions in the choice model, e.g. Arcidiacono (2004 and 2005) and Joensen and Mattana (2017). This is not necessary for our purposes since we want to account for expected wages only in the educational choice process and we are not directly interested in the labor market decisions. A limitation of this approach is that our model does not allow for unobserved heterogeneity in wages.

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. We allow (the log of) wages to depend on the major/college degree, and on major/college degree interactions with gender and years of experience. Furthermore, we include interactions between major and region dummies. Regional effects reflect differences in labor market opportunities across Flanders and serve as a plausible exclusion restriction, i.e. it is reasonable that they affect only wages and do not directly affect utility of attending college or university given that we already control for distance to college/university in the choice model. We do not allow wages to depend on the specific university attended because we do not observe the university or college where the worker obtained his degree. This implies that wages do not capture possible differences in quality between institutions.[22] We obtain the following intuitive findings represented in Table A3 in Appendix. 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

[22] In Flanders, it seems unlikely that there are large differences in returns to graduating from different institutions when controlling for the major and level of the program. All universities and colleges receive public funding on the basis of enrolled students and have regulated quality control at the level of the entire region.

sciences at university (as compared with social sciences or arts). Males earn on average higher wages, but the wage gap is smaller with a college and especially university major. Finally, wages increase with years of experience (seniority), and this increasing wage path is steeper with a college and especially a university major.

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.[23] We estimate the model based on a random sample of 70% of 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 interacted with the year of study t and a rich set of personal and high school background characteristics interacted with all possible study options.

We briefly summarize the main results here, and present the complete set of results in Table A4 in Appendix. 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%).[24] 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. The interaction effects in the first panel of Table A4 show that students who already obtained one or two credits are more successful in the next period.

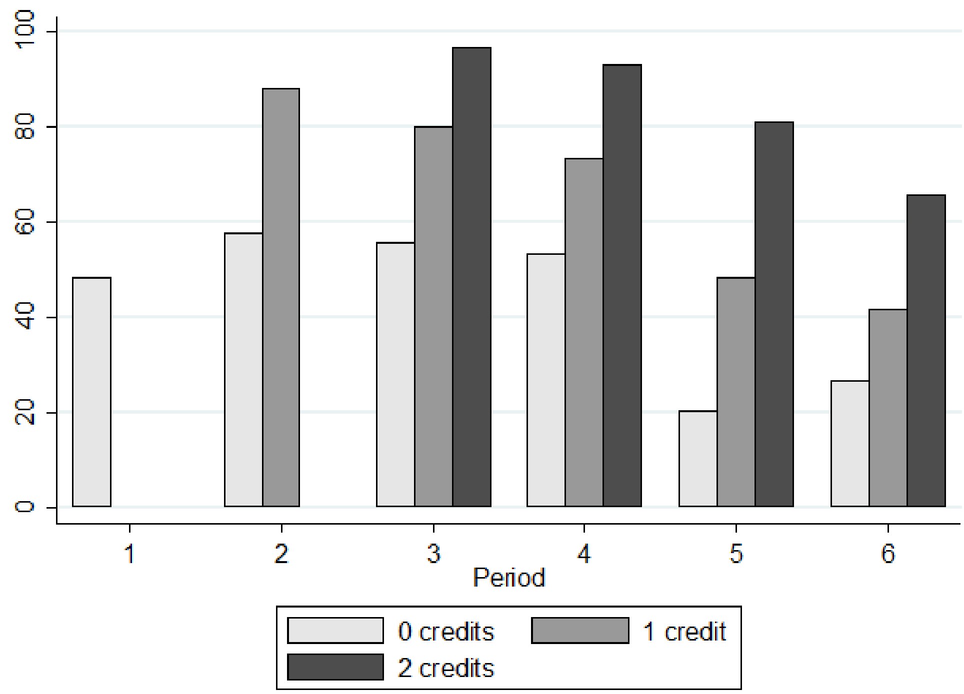
Several personal characteristics play an important role in predicting success rates. Males and students who complete high school with at least one year of delay have significantly lower success rates in all options. Students from a catholic high school are more likely to succeed. High school background also predicts the success probability in higher education: students with a general high school background have 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

[23]This model provides a better fit of the data in terms of the joint log likelihood compared with the basic version of the model without unobserved types. We also estimated a model with three unobserved types. This model provides a slightly better fit of the data in terms of the joint log likelihood compared to the model with two unobserved types. However, the interpretation of the unobserved type coefficients becomes less clear. We therefore present the results of the model with the two unobserved types.

[24]Figure A1 in Appendix provides more detail on the distribution of first-year success rates (when no credits are yet obtained). This confirms that success rates are very low, skewed to low success rates at universities and more evenly distributed at colleges.

sciences imply much higher success rates.[25]

Figure 1: Success probabilities in each period



Finally, we find that there is unobserved heterogeneity (as modeled through different intercepts for the program options for two types): type 2 individuals have significantly higher success rates in programs at college and university. This effect is stronger for university than for college programs. One might therefore interpret the type 2 individuals as "academic types". We return to this interpretation when discussing the results from the dynamic discrete choice model.

Table A5 in Appendix illustrates that this regression predicts success quite well. The table compares the binary success outcome observed in the data with the success probabilities predicted by our model. In 80.7% of the observations, the model correctly predicts success. In 13.8% of the observations, the student fails while our model predicts success (type 1 error). Finally, in 5.5% of the observations, the student succeeds while our model predicts failure (type 2 error).

[25] As less than 2% of students from technical, artistic or vocational high school tracks start at university, we include only dummies for programs in the academic high school track as determinants of success in university programs. As more students from the technical, artistic and vocational track enroll in college programs, we allow for a different effect of programs in other tracks on success at college programs. Therefore, the base category of high school options differs between university and college programs.

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 3 shows the empirical results. Because the model has a large number of parameters, Table 3 shows only 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 3 does not show the estimated effects of the personal characteristics on the utility of the four university and college majors (which amount to 10 demographic variables interacted with 4 majors at university and 16 demographic variables interacted with 4 majors at college). We will briefly discuss these here, and refer to Table A6 in Appendix for the complete set of results.

Table 3 shows that it is important to control for unobserved heterogeneity. From the intercepts for the program options, we see that type 2 individuals obtain more utility from studying than type 1 individuals. This effect is stronger for university programs than for college programs. In the previous section, we already saw that type 2 individuals have higher success rates in all options. Type 2 can thus be interpreted as the academic type. They are more likely to participate in higher education and they also have higher success rates. The probability of being the academic type is higher for individuals who have graduated from academic high school programs and students who have graduated from high school without study delay.

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. Study performance affects the value of studying through two channels. First, it directly increases the utility of studying. Second, as seen in the previous section, it increases success in later periods and makes it more likely that students will obtain a degree.

Table 3: Dynamic discrete choice model

Variables		Coef.	St. error	Coef.	St. error
Unobserved type alternative-specific constants					
		type 1		type 2	
SCI UNIV		-12.020*	(0.273)	-3.890*	(0.218)
BIOM UNIV		-12.007*	(0.286)	-3.716*	(0.239)
SSCI UNIV		-10.448*	(0.195)	-2.384*	(0.115)
ARTS UNIV		-10.946*	(0.241)	-2.611*	(0.174)
SCI COLL		-5.022*	(0.113)	-2.356*	(0.128)
BIOM COLL		-4.706*	(0.149)	-1.735*	(0.163)
SSCI COLL		-2.416*	(0.055)	-0.083	(0.062)
ARTS COLL		-7.440*	(0.251)	-1.528*	(0.207)
type m probability (π_m)		54.7%		45.3%	
Utility parameters					
student characteristics (α_1^j)		included, see Table A6			
travel distance (α_2)		-0.289*	(0.004)		
credits (α_3)		1.312*	(0.035)		
earnings (α_5)		0.581*	(0.050)		
Switching parameters (α_4)					
d_t^j	d_{t-1}^j				
SCI	BIOM	-4.120*	(0.133)		
	SSCI	-3.901*	(0.092)		
	ARTS	-4.363*	(0.216)		
BIOM	SCI	-3.229*	(0.118)		
	SSCI	-3.630*	(0.093))		
	ARTS	-4.991*	(0.295)		
SSCI	SCI	-2.878*	(0.066)		
	BIOM	-3.631*	(0.086)		
	ARTS	-3.130*	(0.079)		
ARTS	SCI	-3.319*	(0.165)		
	BIOM	-4.360*	(0.218)		
	SSCI	-3.367*	(0.104)		
UNIV	COLL	-4.748*	(0.117)		
COLL	UNIV	-1.237*	(0.045)		
β		0.95	(0)		

Note: Sample of 70% 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

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 from arts to biomedical (and vice versa) is 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. Students who complete high school with at least one year of delay are less likely to enroll in higher education. Students from a catholic high school are more likely to start at higher education.

5.3 Model validation

Before performing our policy counterfactuals, we assess how well the model predicts the actual outcomes. We perform both an in-sample and an out-of-sample assessment of two versions of the model. The first version is the basic model where we do not control for unobserved heterogeneity. The second version of the model includes two unobserved types to control for persistent unobserved heterogeneity and uses the individual type probabilities as weights in the prediction of choices and success. Both models predict choices and study outcomes reasonably well.

The results of the in-sample validation of both models are shown in Table 4. For example, according to the last column, 65.0% of the high school students enroll in higher education, while the basic model predicts 72.0% and the second model with unobserved types predicts 66.4%. Similarly, 25.0% of the high school students obtain their diploma within three years, and the first and second version of the model predict numbers that are close, 28.1% and 25.3% respectively. For more detailed predictions regarding university and college enrollment (first and second column of Table 4), the second model continues to perform well, whereas the basic model now substantially overpredicts college enrollment. In Table A7 in appendix, we show the results of our out-of-sample validation.[26] We predict choices and study outcomes

[26] To assess how the model performs out-of-sample, we solve the model for the sample of students not used in the estimation procedure. We randomly assign students to one of the unobserved types according to the

for the sample of students not used in the estimation of the model. Both models also perform reasonably well in predicting out-of-sample outcomes.

Table 4: Model validation

	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[a] of basic dynamic model (percentage)			
Enrollment	18.3	53.7	72.0
Success after 1 year	9.4	26.3	35.7
Diploma after 3 years	7.4	20.7	28.1
Diploma after 6 years	13.1	38.7	51.8
Predictions[a] of dynamic model with 2 unobserved types (percentage)			
Enrollment	23.6	42.8	66.4
Success after 1 year	12.2	20.1	32.3
Diploma after 3 years	9.9	15.4	25.3
Diploma after 6 years	16.5	29.5	46.0

Note: Observed and predicted outcomes are expressed as percentages of 2001 high school graduates.

[a] In-sample predictions are based on the 70% estimation sample of the data.

Finally, both models also perform well in predicting the more detailed university/college and major choices, both in- and out-of-sample, as shown in Table A8 in appendix. However, the basic model overestimates enrollment and degree completion in social science programs at colleges.[27]

6 Counterfactual analysis

We use the estimates of our model to evaluate the effects of alternative, hypothetical admission policies in higher education. We use the dynamic model with the two unobserved types

unobserved type distribution estimated by the model. We repeat this procedure 100 times and compute average study decisions and study outcomes.

[27] Adding a third unobserved type to the model, does not lead to better predictions of enrollment decisions and study outcomes relative to the model with two unobserved types.

because these types significantly affect choices and success. As discussed above, this model also provides a better fit of the data and performs better in predicting enrollment and degree completion. We consider 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 applies only to universities (where success rates are lower) and not to colleges. Our outcome variable is degree completion within 3 or 6 years. While maximizing degree completion might not be an optimal policy in all respects, it reflects a broader policy objective to maximize attainment in higher education within a reasonable time frame. This counterfactual analysis shows how admission standards influence educational attainment.

After outlining our approach (subsection 6.1), we show the effects of gradually raising admission standards on overall educational attainment and discuss the possible trade-offs (subsection 6.2). Finally, we discuss some possible general equilibrium effects of implementing admission policies (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. admit only 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. Both approaches aim to select students with the best prospects. They may not be perfect measures of expected success, and may therefore not necessarily select the best students.

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.[28] 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 therefore followed a variant 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 pupils can start a college or university major only if they have a predicted success rate of at least 50%. More generally, we can vary the toughness of the admission standard by allowing students to enter

[28] We nevertheless implemented this approach. For example, we imposed admission criteria based on high school background, where only pupils with a high school 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 the 40% entry threshold limited to university programs, which we discuss below.

a program only 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. 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.

Both entry exams and direct admission policies may in practice be based on a richer set of characteristics that a university finds important than the observed ones we include in the model for predicting success. For example, entry exams may test on academic skills, and direct admission policies may be based on the grade obtained in high school: both of these may be captured by the unobserved types. At the same time, not all information would be revealed in practice and entry exams or direct admission policies might be less adequate in predicting success than our approach.

6.2 The impact of raising admission standards

Uniform admission standards Figure 2 shows the impact of uniform admission standards on educational attainment, as predicted by the model. We consider admission thresholds of $X\%$ that are uniform across programs, meaning that students can start only at a specific major at college or university for which they have an expected first-year success rate of at least X%. We vary $X\%$ between 0% (the current situation) and 100% (no one is admitted). Implementing a uniform threshold requires different admission criteria for all programs with a different weight for several skills between study programs in higher education. Figure 2 shows that the enrollment rate decreases as the admission thresholds increase. For example, raising the threshold from 0% to 20% reduces first-year participation from 66.4% to 58.0%, while raising the threshold further from 20% to 40% reduces first-year participation to 51.9%, and raising the threshold from 40% to 60% further reduces enrollment to only 35.0%.

Despite the substantial drop in initial enrollment, successful degree completion essentially remains constant for low admission thresholds, and it decreases only 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 25.3% of high school students receive a degree after three years and 46.0% receive their degree after six years. An admission threshold of 20% *raises* these success rates to respectively 25.8% and

46.1%. A stricter admission standard of 40% further raises degree completion within three years to 26.5%, but reduces total degree completion to 44.8%.

In sum, introducing low or intermediate thresholds (below 25%) reduces first-year overall enrollment, whereas it does not reduce successful degree completion after 3 and 6 years. The intuition for this finding is that the admission thresholds induce students to shift more quickly to programs according to their abilities. Tighter admission standards (above 25%) decrease enrollment further, but also lead to a decrease in degree completion. Note that these specific admission standards might be difficult to implement in practice as this approach presupposes that institutions have information about students' observed and unobserved characteristics. Rather than searching for an optimal admission standard, our counterfactuals illustrate the trade-offs of implementing different admission standards that vary in their toughness.

Figure 2: Uniform admission standards

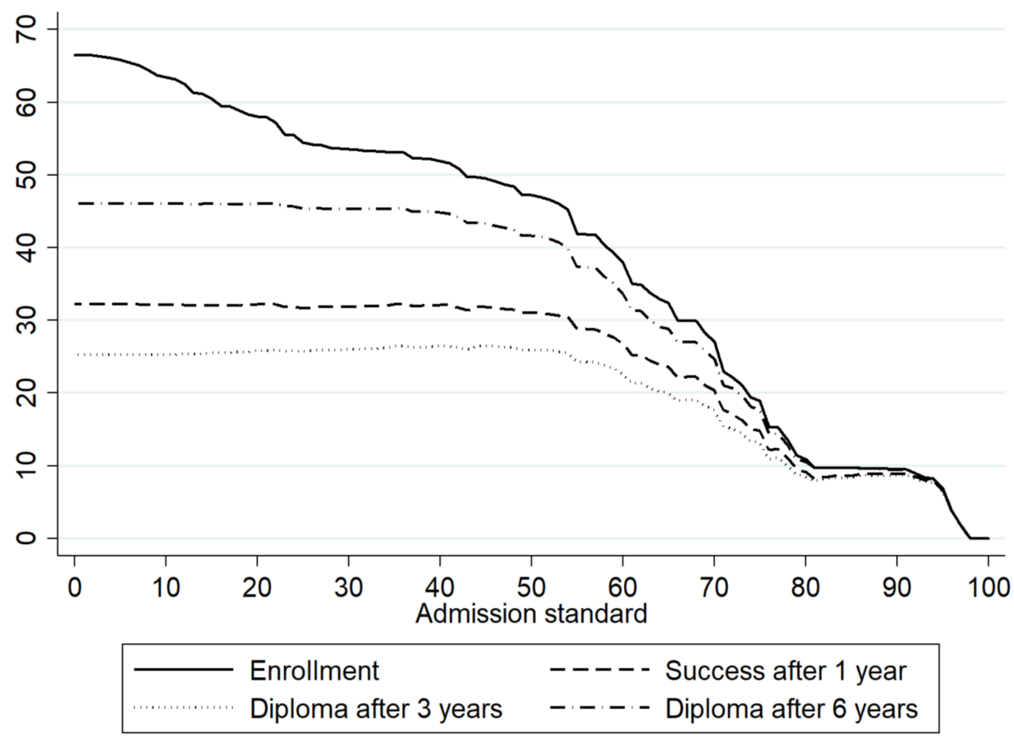


Table 5 provides more detailed information on the impact of the 20% and 40% admission thresholds at universities and colleges (compared with 0% thresholds as in the status quo). The 20% uniform admission threshold reduces first-year participation by 2.7% points at universities and by 5.7% points at colleges. The increase in successful degree completion can be fully attributed to colleges (+0.7% points after three years and +0.5% points after six years); the number of students graduating from universities decreases but by a smaller amount (-0.2% points after three years and -0.4% points after six years). The admission threshold thus induces a shift from universities to colleges: intuitively, students with very low expected success rates at universities (below 20%) will now choose other programs at colleges where they have higher success rates. The admission standard also induces shifts within universities and colleges to programs that better match students' abilities. As a result more students pass the first year, and fewer students end up dropping out without a degree.

The third panel of Table 5 shows the impact of a moderate 40% admission threshold. Total enrollment drops more considerably. Degree completion after three years further increases, but such a threshold would not admit some students who would have obtained their degree after some study delay as total degree completion decreases. Behind this is a shift from university to college degrees.

As a final remark, note that our chosen 20% or 40% admission threshold levels are only illustrative. They should not be literally interpreted as "target" numbers set by the government in every year. They rather refer to the government's degree of ex ante selectivity (or "toughness") when designing an entry exam of direct admission policy.

Discriminatory admission standards Figure A2 in Appendix shows the impact on educational attainment of a similar experiment, i.e. discriminatory admission thresholds that apply only to university programs and not to college programs. This shows that such admission thresholds 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, but labor market returns are lower.

The fourth and fifth panel of Table 5 show the changes in enrollment and successful completion rates at university and college under an admission threshold limited to programs at university of respectively 20% and 40%. Discriminatory admission thresholds of 20% lead to a decrease in first-year participation, but by less than under a similar uniform threshold of 20% (-0.4% points instead of -8.4% points). Total degree completion increases, with a shift from university degrees (-0.5%) to college degrees (+1%). A stricter admission threshold of 40% leads to an even larger increase in degree completion (+1.1%), with an even stronger shift from university to college degrees.

Table 5: Uniform admission standards

	university	college	total
Predictions of dynamic model (percentage)			
Enrollment	23.6	42.8	66.4
Success after 1 year	12.2	20.1	32.3
Diploma after 3 years	9.9	15.4	25.3
Diploma after 6 years	16.5	29.5	46.0
Uniform admission standard of 20% (percentage point change)			
Enrollment	-2.7	-5.7	-8.4
Success after 1 year	-0.4	+0.3	-0.1
Diploma after 3 years	-0.2	+0.7	+0.5
Diploma after 6 years	-0.4	+0.5	+0.1
Uniform admission standard of 40% (percentage point change)			
Enrollment	-7.6	-6.9	-14.5
Success after 1 year	-1.9	+1.8	-0.1
Diploma after 3 years	-1.1	+2.3	+1.2
Diploma after 6 years	-2.5	+1.3	-1.2
Admission standard of 20% at university (percentage point change)			
Enrollment	-2.7	+2.3	-0.4
Success after 1 year	-0.4	+1.2	+0.8
Diploma after 3 years	-0.2	+0.9	+0.7
Diploma after 6 years	-0.5	+1.0	+0.5
Admission standard of 40% at university (percentage point change)			
Enrollment	-7.6	+7.0	-0.6
Success after 1 year	-1.9	+4.1	+2.2
Diploma after 3 years	-1.1	+3.1	+2.0
Diploma after 6 years	-2.5	+3.6	+1.1

Note: Predicted outcomes are the in-sample predictions, the same as in Table 4, expressed as percentages of 2001 high school graduates. Predicted outcomes of admission policies are expressed as percentage point changes relative to the status quo.

In sum, low admission standards decrease enrollment without lowering degree completion. Admission standards force students to start at programs in which they have higher success rates. Students who perform well in the first year are more likely to continue the program and have a higher probability of obtaining a degree. In a system without admission standards, many students drop out without obtaining a degree. Too strict admission standards may however decrease degree completion or imply shifts from university to college degrees.[29]

The above discussion focused on how admission standards induce shifts from universities to colleges, raising student success rates. The admission standards can also induce shifts within universities and within colleges to different majors. This sorting can for example discourage students to start at more lucrative programs, such as sciences or biomedical sciences. In Table A9 in appendix, we present percentage point changes in enrollment and graduation rates for all majors under the 20% and 40% uniform and discriminatory admission standard. We find that admission standards do not lead to switches to less lucrative majors. Under the 20% uniform admission standard, the number of graduates in science programs at university decreases by only 0.1% points while the number of graduates in the corresponding science major at college increases by 0.4% points. Total discounted lifetime earnings are higher under the 20% and 40% uniform admission standard, but lower under the 40% admission standard limited to university programs.[30] Moderate admission standards increase total discounted earnings because they prohibit students from starting at programs in which they have low expected success rates. First, students with very low success rates now directly start working instead of enrolling in higher education and dropping out without a degree. Second, students start at programs that better match with their abilities and they are therefore more likely to graduate without delay and enter the labor market at an earlier age. Stricter admission standards will decrease total discounted earnings.

The proposed admission standards can lead to direct and indirect cost savings for the government. Under admission thresholds, fewer students enroll in higher education and more students start at programs in which they have a higher success rate and are therefore more likely to graduate on time. This leads to a considerable reduction in variable cost subsidies to higher education.[31] Furthermore, there can be additional indirect savings indirect savings

[29] Arcidiacono et al. (2016) show that providing more information to students when they make their enrollment decisions also increases degree completion as students learn about their ability while in college. We cannot assess this as our model does not allow for learning about ability.

[30] The uniform admission standards of 20% and 40% respectively increase average total discounted lifetime earnings by 0.8% and 0.6%. The discriminatory admission standards of 20% increases average total discounted lifetime earnings by 0.2%. However, the discriminatory standard of 40% decreases average total discounted lifetime earnings by 0.2%. This decrease in earnings can be explained by the fact that a strict admission standard limited to university programs induces a switch from university to college programs with lower expected earnings.

[31] We can quantify these cost savings based on variable cost subsidies that are reported in Kelchtermans and Verboven (2010), and depend on the type of study program (e.g. social sciences have lower variable cost subsidies than engineering). Under the status quo, we compute that total discounted variable cost subsidies are 6252 euro per high school graduate. The 20% uniform admission standard decreases variable cost subsidies by more than 7% to 5791 euro per high school graduate. The 40% uniform admission standard

from well-designed admission standards stemming from a decrease in foregone earnings in the labor market because more students graduate on time.

A negative consequence of introducing admission standards is that they restrict the choice set of some students. Students with low expected success rates will be excluded from some or all higher education programs. Restricting the choice set decreases students' welfare as some students will not have the option anymore to start at their most prefered study program. The total welfare effect of introducing admission standards that do not decrease degree completion may therefore not necessarily be positive, and further warrants the consideration of only low admission standards.

6.3 General equilibrium effects?

Our counterfactual analysis assumed that the admission thresholds do not affect high school choices, peer group composition and quality in higher education, and labor market outcomes. Analyzing how admission policies affect these outcomes is not possible with our dataset. Based on the institutional context, we assess how this could affect our results.

First, introducing admission thresholds may affect choices in high school and induce students to choose high school programs that provide the best preparation for the entry exams, and they may also stimulate study effort during high school. However, we argue that introducing moderate entry exams would in practice have limited effects on high school choices in Flanders. First, entry exams as currently being proposed focus on testing intrinsic skills rather than specific skills acquired in high school. Second, pupils are to an important extent selected in the specific high school programs based on their performance in previous years, so they have little freedom to choose a more demanding program if they expect entry exams for college or university. Third, our counterfactuals consist of only moderate admission standards, so that any anticipation effects would be small. In case students would exert more effort and graduate from programs that prepare better for higher education, we argue that our policy counterfactuals would underestimate the gains from admission standards. More students will successfully participate and degree completion will further increase.

Second, admission standards may involve positive peer effects and therefore further increase degree completion, because fewer students with low success rates will enroll. Positive peer effects are more likely with uniform admission standards, because average class size will be smaller across all programs. This could increase the quality of education and further

decrease variable cost subsidies by about 15% to 5253 euro. The discriminatory standards have a smaller effect on costs per high school graduate, because they apply to a smaller group of students. These numbers should be interpreted with caution as the variable subsidy costs might not necessarily reflect economic variable costs.

increase degree completion. With discriminatory standards, the role of peer effects may be ambiguous. The shift from university to colleges implies positive peer effects at universities. At colleges, there may be positive effects from the stronger students shifting out from university, but negative effects because class size increases. This increase in class size might decrease the quality of education at colleges or force them to implement stricter ex-post screening standards due to problems of capacity constraints. This could have a negative effect on degree completion if colleges are not compensated for the increase in enrollment.

Third, introducing admission standards also affects degree completion and can therefore lead to labor market changes. Strict admission standards lead to a lower number of university graduates. This may raise the wages for university graduates, which may in turn make university programs more attractive. However, we argue that introducing *moderate* admission standards will have a very limited impact on wages. First, as shown in Table A9, a moderate admission threshold has only a very limited impact on the number of graduates in each major at college or university. Second, as a robustness check we repeated our counterfactual analysis after assuming that wages for university graduates increase by 10%. This has only a small impact on enrollment (+0.4%points). Hence, we do not expect that moderate admission standards would lead to important wage changes, and even if this would be the case, it would have a negligible impact on study decisions.

Finally, changing admission standards might affect the signalling value of obtaining a higher education degree, and thereby influencing the wage returns. This could be the case if admission standards differ between instituions with some institutions imposing highly selective admission standards as in the U.S. We argue that this seems unlikely in our context as the admission standards we propose do not differ between institutions. As low or moderate admission standards do not lead to a lower number of graduates, it seems unlikely that this would affect the signaling value. Introducing high standards could increase the signaling value of higher education as only the most intelligent students would be able to start higher education and thereby signaling their high ability.

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 substantially decreases unsuccessful enrollment without lowering degree completion. First, we consider a uniform admission standard that applies to both colleges and universities. A modest uniform admission standard of 20% decreases enrollment by 8.4% points and at the same time increases overall educational attainment after three years by up to 0.5% points and educational attainment after six years by up to 0.1% points. This is because the admission threshold induces a shift in the first year from universities to colleges, by students who would have had a very low probability of success. A stricter admission threshold of 40% has a larger impact on enrollment (-14.5% points) but reduces total degree completion after six years by 1.2% points.

Second, we consider a discriminatory admission standard which applies only to universities and not to colleges. The 20% and 40% admission thresholds limited to university programs have a smaller impact on total enrollment of respectively -0.4% points and -0.6% points, but lead to a higher number of graduates (+0.5% points and +1.1% point). However, this increase in educational attainment involves a shift from universities to colleges: the 40% discriminatory threshold leads to an increase in college diplomas (+3.6% points), which comes at the expense of university diplomas (-2.5% points) and may not be desirable as total discounted lifetime earnings of students will be lower.

The economic intuition behind our findings is as follows. Admission standards prevent students with low expected success rates from enrolling in higher education and induce students to start at programs that better match with their abilities. This increases first-year success rates and therefore the probability of continuing and obtaining a degree. In contrast, under the current system without admission standards, many students drop out after being unsuccessful in their first year, especially at college programs.

Well-designed admission standards can thus lead to resource savings as less students enroll and more students graduate without study delay. 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. These cost savings can also be used to improve the quality of education to increase the number of graduates even further. 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. A complete welfare analysis would give a more complete understanding of the tradeoff between the cost savings of admission policies with the decrease in students' welfare caused by the fact that some students do not have the option anymore to attend higher education.

Finally, our findings also provide lessons to other countries that use no or very weak admission standards. For example in Italy, Switzerland and Austria, all high school graduates who passed a national exam are eligible to start at most programs in higher education. A shift towards more moderate admission standards might also decrease unsuccessful degree completion in these countries without decreasing total degree completion. Our findings also have implications for countries that use stronger or discriminatory admission standards like in the U.S. We show that too strict admission standards may imply large shifts between study programs and can lead to a decrease in the total discounted lifetime income of students if students are discouraged from starting at study programs with higher wage returns.

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Appendix: 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

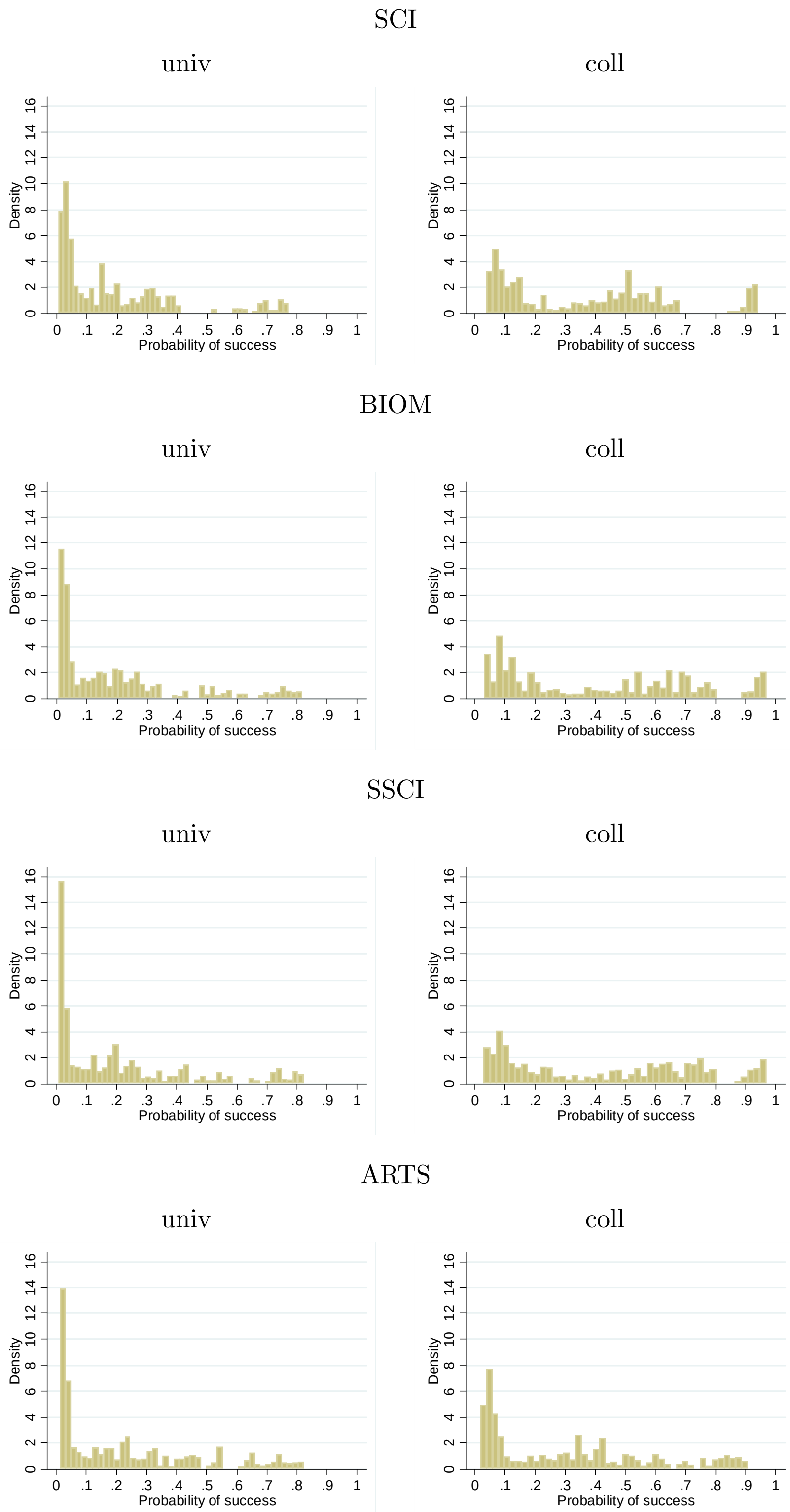

Table A4: The probability of success

Period	credits	Coefficient	St. error
period 2	0	0.523*	(0.037)
	1	1.739*	(0.044)
period 3	0	0.289*	(0.065)
	1	1.316*	(0.047)
	2	2.979*	(0.070)
period 4	0	0.152	(0.142)
	1	0.942*	(0.071)
	2	2.367*	(0.072)
period 5	0	-1.340*	(0.354)
	1	-0.166	(0.115)
	2	1.332*	(0.081)
period 6	0	-1.125*	(0.514)
	1	-0.391*	(0.183)
	2	0.659*	(0.133)

Note: Sample of 70% 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	-3.353*	(0.321)	-3.602*	(0.324)	-3.926*	(0.199)	-3.396*	(0.243)
type 2 interaction	2.592*	(0.063)	2.592*	(0.063)	2.592*	(0.063)	2.592*	(0.063)
male	-0.352*	(0.146)	-0.341*	(0.120)	-0.377*	(0.069)	-0.441*	(0.127)
general HS[a]								
clas + math	1.732*	(0.292)	1.928*	(0.293)	2.509*	(0.188)	2.230*	(0.243)
clas + lang	0.982	(1.153)	1.181*	(0.425)	2.025*	(0.189)	2.000*	(0.226)
sci + math	1.680*	(0.270)	2.136*	(0.283)	2.418*	(0.189)	1.820*	(0.300)
math + lang	0.045	(0.327)	0.686*	(0.309)	1.111*	(0.183)	0.867*	(0.251)
econ + math	0.116	(0.368)	0.937*	(0.407)	1.276*	(0.182)	1.321*	(0.434)
econ + lang	-1.157	(3.743)	-0.610	(0.722)	0.699*	(0.185)	0.572*	(0.242)
human	-0.181	(2.341)	-0.252	(0.861)	0.550*	(0.195)	0.381	(0.267)
repeated	-0.588*	(0.244)	-0.759*	(0.211)	-0.622*	(0.089)	-0.445*	(0.161)
catholic HS	0.250	(0.144)	0.374	(0.173)	0.362*	(0.087)	0.116	(0.152)

Note: Sample of 70% 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	-2.482*	(0.271)	-2.349*	(0.326)	-2.322*	(0.103)	-2.698*	(0.498)
type 2 interaction	2.094*	(0.038)	2.094*	(0.038)	2.094*	(0.038)	2.094*	(0.038)
male	-0.270*	(0.099)	-0.462*	(0.118)	-0.716*	(0.039)	-0.342*	(0.138)
general HS[b]								
clas + math	2.864*	(0.301)	3.120*	(0.425)	3.449*	(0.179)	2.507*	(0.558)
clas + lang	2.820*	(0.417)	2.524*	(0.424)	2.968*	(0.141)	2.685*	(0.506)
sci + math	2.945*	(0.260)	3.280*	(0.359)	3.185*	(0.136)	2.210*	(0.555)
math + lang	0.497	(0.301)	1.029*	(0.365)	1.278*	(0.122)	0.848	(0.518)
econ + math	0.658*	(0.291)	0.881*	(0.393)	1.240*	(0.116)	1.255	(0.685)
econ + lang	0.254	(0.299)	0.667	(0.359)	1.105*	(0.100)	0.081	(0.513)
human	0.218	(0.321)	0.405	(0.354)	1.025*	(0.109)	0.467	(0.527)
technical HS[b]								
management	0.353	(0.296)	-0.074	(0.377)	0.876*	(0.099)	-0.113	(0.537)
sci + tech	0.588*	(0.262)	0.442	(0.351)	0.531*	(0.128)	1.917	(1.909)
social + tech	0.518	(0.357)	0.482	(0.345)	0.986*	(0.114)	-0.161	(0.752)
technics	1.263*	(0.254)	0.881*	(0.402)	0.728*	(0.149)	0.455	(0.668)
other tech	0.402	(0.326)	0.416	(0.338)	0.870*	(0.108)	-0.442	(0.640)
artistic HS[b]	0.280	(0.306)	0.853	(1.075)	0.170	(0.185)	0.760	(0.488)
repeated	-0.499*	(0.073)	-0.630*	(0.112)	-0.473*	(0.039)	-0.578*	(0.163)
catholic HS	0.216*	(0.080)	0.474*	(0.139)	0.232*	(0.046)	0.204	(0.154)

Note: Sample of 70% of 55,524 high school graduates, up to 6 periods

* statistical significance at 5% level.

[b] Base category = vocational secondary education

Table A5: Prediction of success rates

		Observed success	
		Pass	Fail
Predicted success	Pass	63.9%	13.8%
	Fail	5.5%	16.8%

Note: We compare predicted success rates with observed succes of all students in all periods. The model predicts success if the predicted success rate is at least 50%.

Dynamic discrete choice model

Table A6: Dynamic discrete choice model

Variables		Coef.	St. error
Utility parameters			
travel costs (α_2)		-0.289*	(0.002)
credits (α_3)		1.312*	(0.024)
earnings (α_5)		0.581*	(0.028)
Switching costs			
d_t^j	d_{t-1}^j		
SCI	BIOM	-4.120*	(0.133)
	SSCI	-3.901*	(0.092)
	ARTS	-4.363*	(0.216)
BIOM	SCI	-3.229*	(0.118)
	SSCI	-3.630*	(0.093))
	ARTS	-4.991*	(0.295)
SSCI	SCI	-2.878*	(0.066)
	BIOM	-3.631*	(0.086)
	ARTS	-3.130*	(0.079)
ARTS	SCI	-3.319*	(0.165)
	BIOM	-4.360*	(0.218)
	SSCI	-3.367*	(0.104)
UNIV	COLL	-4.748*	(0.117)
COLL	UNIV	-1.237*	(0.045)
type 1		54.7%	
type 2		45.3%	
β		0.95	(0)

Note: Sample of 70% 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 A6: 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	-12.020*	(0.273)	-12.007*	(0.286)	-10.448*	(0.195)	-10.946*	(0.241)
constant type 2	-3.890*	(0.218)	-3.716*	(0.239)	-2.384*	(0.115)	-2.611*	(0.174)
male	1.013*	(0.083)	-0.349*	(0.079)	-0.034	(0.053)	0.056	(0.073)
general HS[a]								
clas + math	9.451*	(0.238)	9.646*	(0.198)	9.943*	(0.199)	8.557*	(0.220)
clas + lang	6.795*	(0.457)	8.367*	(0.267)	9.159*	(0.201)	9.348*	(0.220)
sci + math	9.611*	(0.224)	9.782*	(0.224)	8.431*	(0.191)	7.506*	(0.225)
math + lang	1.861*	(0.186)	2.168*	(0.183)	2.034*	(0.112)	1.628*	(0.154)
econ + math	1.490*	(0.212)	1.393*	(0.215)	2.302*	(0.112)	0.507*	(0.208)
econ + lang	-0.628	(0.489)	0.404	(0.279)	1.978*	(0.101)	1.280*	(0.146)
human	0.167	(0.474)	0.553	(0.316)	1.988*	(0.109)	1.416*	(0.162)
repeated	-0.745*	(0.133)	-0.211	(0.133)	-0.173*	(0.065)	-0.137	(0.099)
cath	0.025	(0.095)	0.294*	(0.107)	0.047	(0.079)	0.030	(0.094)

Note: Sample of 70% 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 A6: 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	-5.022*	(0.113)	-4.706*	(0.149)	-2.416*	(0.055)	-7.440*	(0.251)
constant type 2	-2.356*	(0.128)	-1.735*	(0.163)	-0.832*	(0.062)	-1.528*	(0.207)
male	0.739*	(0.055)	-0.844*	(0.062)	-0.126*	(0.030)	-0.123	(0.077)
general HS[b]								
clas + math	3.088*	(0.163)	3.252*	(0.194)	0.993*	(0.120)	5.523*	(0.286)
clas + lang	2.024*	(0.208)	3.052*	(0.205)	1.546*	(0.113)	6.460*	(0.262)
sci + math	3.585*	(0.130)	3.498*	(0.168)	1.304*	(0.092)	5.178*	(0.274)
math + lang	1.037*	(0.146)	1.232*	(0.168)	0.658*	(0.072)	0.926*	(0.214)
econ + math	0.938*	(0.142)	0.845*	(0.185)	0.908*	(0.070)	-0.186	(0.262)
econ + lang	0.448*	(0.143)	1.120*	(0.157)	1.248*	(0.057)	0.768*	(0.218)
human	0.715*	(0.150)	1.490*	(0.157)	1.148*	(0.062)	0.693*	(0.223)
technical HS[b]								
management	0.706*	(0.139)	0.890*	(0.170)	1.459*	(0.051)	0.296	(0.235)
sci + tech	1.487*	(0.124)	1.295*	(0.167)	0.276*	(0.068)	-1.425*	(0.323)
social + tech	1.402*	(0.168)	2.713*	(0.165)	1.685*	(0.069)	0.473	(0.340)
technics	2.344*	(0.110)	1.401*	(0.174)	-0.031	(0.073)	0.073	(0.294)
other tech	0.605*	(0.149)	1.694*	(0.164)	1.007*	(0.057)	-0.025	(0.282)
artistic HS[b]	0.995*	(0.153)	-0.680*	(0.329)	-0.334*	(0.106)	1.292*	(0.200)
repeated	-0.261*	(0.053)	-0.249*	(0.066)	-0.165*	(0.030)	0.062	(0.090)
cath	0.204*	(0.053)	0.230*	(0.073)	0.091*	(0.033)	0.040	(0.085)

Note: Sample of 70% 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

Model validation and policy counterfactuals

Table A7: Out-of-sample validation

	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
Out-of-sample[a] predictions of basic model (percentage)			
Enrollment	18.1	54.1	72.2
Success after 1 year	9.3	26.6	35.9
Diploma after 3 years	7.3	21.1	28.4
Diploma after 6 years	12.9	39.3	52.2
Out-of-sample[a] predictions of model with 2 unobserved types (percentage)			
Enrollment	23.8	42.9	66.7
Success after 1 year	12.2	20.2	32.4
Diploma after 3 years	9.9	15.5	25.4
Diploma after 6 years	16.6	29.7	46.3

Note: Observed and predicted outcomes are expressed as percentages of 2001 high school graduates.

[a] Out-of-sample predictions are based on the sample not used for estimation.

Table A8: Model validation: major choices

	university				college			
	SCI	BIOM	SSCI	ARTS	SCI	BIOM	SSCI	ARTS
Observed choices and study outcomes (percentage)								
Enrollment	3.7	4.2	10.0	3.1	9.0	4.5	27.4	3.0
Success after 1 year	2.0	2.4	4.9	1.6	4.3	2.5	12.5	1.4
Diploma after 3 years	1.6	2.2	4.0	1.5	3.0	1.9	9.9	0.9
Diploma after 6 years	2.4	2.9	6.3	2.2	5.6	3.3	19.6	1.5
In-sample validation[a]								
Basic model (percentage)								
Enrollment	4.8	1.9	10.3	1.4	9.7	2.6	39.8	1.6
Success after 1 year	2.4	1.1	5.2	0.7	4.6	1.4	19.5	0.7
Diploma after 3 years	1.8	0.9	4.3	0.4	3.4	0.9	15.8	0.5
Diploma after 6 years	3.3	1.6	7.5	0.6	6.2	1.4	30.3	0.8
Model with 2 unobserved types (percentage)								
Enrollment	4.6	2.4	15.2	1.5	9.8	4.7	25.9	2.4
Success after 1 year	2.6	1.6	7.2	0.7	4.8	2.7	11.5	1.1
Diploma after 3 years	2.1	1.5	5.9	0.5	3.5	2.0	9.1	0.8
Diploma after 6 years	3.3	2.0	10.4	0.7	6.7	3.4	17.8	1.6
Out-of-sample validation[b]								
Basic model (percentage)								
Enrollment	4.8	1.8	10.1	1.4	9.9	2.6	40.1	1.5
Success after 1 year	2.4	1.1	5.1	0.7	4.7	1.5	19.8	0.7
Diploma after 3 years	1.8	0.9	4.2	0.4	3.5	1.0	16.1	0.5
Diploma after 6 years	3.4	1.5	7.4	0.6	6.4	1.4	30.7	0.8
Model with 2 unobserved types (percentage)								
Enrollment	4.8	2.2	15.2	1.5	9.9	4.8	26.0	2.3
Success after 1 year	2.8	1.5	7.2	0.7	4.8	2.7	11.6	1.0
Diploma after 3 years	2.3	1.4	5.8	0.4	3.5	2.1	9.2	0.7
Diploma after 6 years	3.6	1.9	10.4	0.6	6.8	3.4	18.0	1.5

Note: Observed and predicted outcomes are expressed as percentages of 2001 high school graduates.

[a] In-sample predictions are based on the 70% estimation sample of the data.

[b] Out-of-sample predictions are based on the sample not used for estimation

Table A9: Policy counterfactuals

	university				college			
	SCI	BIOM	SSCI	ARTS	SCI	BIOM	SSCI	ARTS
Predictions of dynamic model (percentage)								
Enrollment	4.6	2.4	15.2	1.5	9.8	4.7	25.9	2.4
Success after 1 year	2.6	1.6	7.2	0.7	4.8	2.7	11.5	1.1
Diploma after 3 years	2.1	1.5	5.9	0.5	3.5	2.0	9.1	0.8
Diploma after 6 years	3.3	2.0	10.4	0.7	6.7	3.4	17.8	1.6
Uniform admission standard of 20% (percentage point change)								
Enrollment	-0.9	-0.2	-1.5	-0.2	-0.1	-0.4	-5.3	-0.2
Success after 1 year	-0.1	-0.0	-0.2	-0.0	+0.4	-0.0	-0.1	+0.1
Diploma after 3 years	-0.0	-0.0	-0.2	-0.1	+0.4	+0.1	+0.2	+0.1
Diploma after 6 years	-0.1	-0.0	-0.3	-0.0	+0.4	+0.0	+0.0	+0.1
Uniform admission standard of 40% (percentage point change)								
Enrollment	-1.1	-0.4	-5.6	-0.5	-0.7	-0.1	-5.6	-0.5
Success after 1 year	-0.2	-0.1	-1.5	-0.1	+0.3	+0.4	+1.2	-0.1
Diploma after 3 years	-0.1	-0.1	-1.0	-0.1	+0.4	+0.4	+1.6	-0.1
Diploma after 6 years	-0.2	-0.0	-2.1	-0.1	+0.3	+0.3	+1.0	-0.3
Admission standard of 20% at university (percentage point change)								
Enrollment	-0.9	-0.2	-1.5	-0.2	+0.9	+0.2	+1.0	+0.3
Success after 1 year	-0.1	-0.0	-0.2	-0.0	+0.5	+0.1	+0.6	+0.1
Diploma after 3 years	-0.0	-0.0	-0.2	-0.1	+0.4	+0.1	+0.4	+0.1
Diploma after 6 years	-0.1	-0.0	-0.3	-0.0	+0.4	+0.0	+0.4	+0.2
Admission standard of 40% at university (percentage point change)								
Enrollment	-1.1	-0.4	-5.6	-0.5	+1.3	+0.8	+4.4	+0.6
Success after 1 year	-0.2	-0.1	-1.5	-0.1	+0.7	+0.5	+2.7	+0.2
Diploma after 3 years	-0.1	-0.1	-1.0	-0.1	+0.5	+0.4	+2.0	+0.2
Diploma after 6 years	-0.2	-0.0	-2.1	-0.1	+0.5	+0.4	+2.4	+0.3

Note: Predicted outcomes are the in-sample predictions, the same as in Table A8, expressed as percentage point changes relative to the status quo.

Figure A2: Admission standards limited to programs at university