Admissions Constraints and the Decision to Delay University

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Abstract

We investigate whether delaying entrance into university is affected by features of an admissions system, which are prevalent across the Nordic countries. Using Danish administrative data, we estimate a dynamic discrete choice model, in which students choose, if admitted, whether to enter one of 30 programs or delay. We use the model to examine delaying choices under different simulated admissions policies. Our experiments suggest that only 21% of students who delay do so because of admissions restrictions. Furthermore, although students respond to admissions incentives, our results imply that such policies are unlikely to substantially change the overall distribution of delay.

Keywords: University admissions policies; Timing of university enrollment
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1 Introduction

Compared to the amount of attention that has been directed toward understanding the decision to attend university, the issue of *when* to attend receives relatively little attention. Yet, taking a year or two off between high school and university is observed in many countries. The practice of delaying entrance into higher education is particularly common in the Nordic countries (Hauschildt et al., 2015). In this paper, we focus on high school graduates in Denmark, where delaying university is a fairly widespread practice that increased in prevalence during the 1980's and 1990's. In the 2007 high school graduating cohort, among those who attended university within six years, only 1 in 5 went directly from high school. Moreover, there is some evidence in the literature that delaying can be individually costly (Holmlund et al., 2008).

In this paper, we investigate the extent to which the decision to delay entrance into university is affected by admissions restrictions using the Danish university admissions system from the early 1980's. This system remains relevant because many of its key features are currently employed in Denmark and other Nordic countries. In the policy environment we study, the number of places in any given program were fixed on an annual basis. When student demand for programs exceeded the supply, admissions were allocated on the basis of students' high school grade point average (GPA). Because demand and supply varied from year to year, the GPA required to enter a given program also fluctuated. For this reason, and because of other features of the policy that rewarded full-time employment in admissions, there were incentives for students who may not be admitted to a preferred program in a given year to delay their entrance into university.

In addition to the apparent incentives to delay, we also note that, in administration data, the propensity to delay entrance into university varies substantially with the field of study entered. This empirical pattern further points toward a link between admissions policies and the timing of entrance.

To investigate this link, we develop and estimate a dynamic discrete choice model that is governed by the Danish admissions system in effect during our sample period. In our three-period model, students choose between entering one of 30 university programs at 8 different universities or delaying to the next period. To estimate the model, we use data from the Danish population registers covering students who graduated from high school in the years 1981-1983 and entered university within 2 years. In addition to parametric assumptions, the model is identified using exogenous variation in the minimum GPA required to enter a program. A structural approach is critical in this context because delaying and choosing a field of study are simultaneously determined. Indeed, the decision to delay can be framed as the decision not to enter any field of study in any given year.

We use the model to gauge the extent to which the timing of students' entry into university is affected by admissions constraints, including the risk associated with unpredictable movements in future GPA thresholds. We simulate experiments that compare decisions made in a policy environment with open admissions to different counterfactuals with admissions constraints that are risky in future periods. In these experiments, we hold constant all other aspects of utility so that changes in students' choices can be attributed to the admissions policies.

Compared to the admissions system from the sample period, holding all else constant, we find that the fraction of students delaying by at most two years falls by roughly 6 percentage points in a completely open admissions system. Our structural approach allows us to quantify the gross flows that generate this net effect.

Our simulated counterfactuals suggest that among students who delay entrance into university, roughly 21% do so because of admissions restrictions. This group represents 8.9% of all students in the sample. These students delay by either one or two years, and in the absence of any admissions constraints, we find that most of these delayers would enter directly from high school. We also quantify a less obvious incentive embedded in the admissions system that might discourage delay. In particular, some students, who in an open admissions system would prefer to delay, might enter without delay because of unpredictable fluctuations in future GPA requirements. In our sample, we find that this incentive affects only 1.5% of the students. Thus, the incentives to delay within the admissions system dominate this much smaller effect.

While our model predicts that only 8.9% of the sample delay because of admission restrictions, we find that a further 11.5 percent of the sample would enter a different program in the absence of restrictions. This group would not, however, delay for that possibility when restrictions and risk are present. As a consequence, relaxing admissions restrictions shifts the distribution of field of study, in some cases without also reducing delaying. In particular students flow into Medicine, which consistently has high excess-demand. However, when admissions are open in all programs except Medicine, our counterfactuals suggest that delay falls by roughly the same amount but the shifts in the distribution of field of study are fairly small.

Taken as a whole, our results suggest that students do alter the timing of their entrance into university in response to admissions restrictions. However, as a fraction of all students delaying this group represents a minority. As such, it is unlikely that policies, such as GPA multipliers that confer advantages in admissions for students who enroll directly after high school, will substantially alter the overall distribution of delay.

The rest of the paper proceeds by first reviewing the relevant literature and then by describing, in brief, the Danish schooling system, and the admissions system during our sample period. In the next two sections, we introduce our data and describe the individual characteristics associated with delaying university. In this section, we also document the relationship between delaying and field of study. Next, we introduce the discrete choice model, and explain how it is identified and estimated. In the results section, we begin by discussing how well the model fits the data and can predict changes outside of the sample. We then discuss the main findings from the simulated counterfactual experiments. Finally, we offer some concluding comments.

2 Previous Research

Much of the literature investigating the timing of post-secondary schooling focuses on how delays and interruptions affect earnings and wages. The findings are mixed, depending on the data and the nature of the delay. In a sample of Canadian post-secondary graduates, Ferrer and Menendez (2014) find that post-schooling wages are higher for those who delayed their entry, particularly for those who worked during the delay. In contrast, two U.S. studies suggest that delaying is associated with lower returns to completed schooling, although those losses are not uniform across different levels of schooling. Light (1995) reports that, on average, among white men with the same amount of schooling, those who completed without interruption earned a higher premium. There is no difference, however, in the subgroup of men who completed 12 years of education. In a broader sample including women and minorities, Monks (1997) finds that the returns to education are lower for people who gradate from college after age 25.

Studies with access to panels of earnings have found initial earnings losses that eventually fade away. Using data from a British panel of the cohort born in 1970, Crawford and Cribb (2012) report that delaying higher education by up to three years reduces average earnings at age 30. By age 38, this difference is small and no longer statistically significant. Using Swedish data that is most similar to ours, Holmlund et al. (2008) find that, delaying university by two or more years is associated with lower earnings at age 30. Overtime the earnings gap closes so that delaying has no impact on earnings by age 42. Overall, however, Holmlund et al. (2008) estimate a total loss in the discounted present value of lifetime earnings amounting to 40 to 50% of one year of age-40 earnings.

While earnings and wages are a useful summary statistic for the many ways in which delaying might impact productivity, these outcomes do not provide much direct evidence about why students delay. As Holmlund et al. (2008) suggest, there are a variety of reasons why students may delay including because they were not admitted into their preferred program, which is the issue we pursue in this paper.

A recent but rapidly growing literature suggests that the decision of which field of study to enter is as, if not more, important as the decision to pursue higher education. Indeed, wage differences across fields of study have been found to be as large as the average return to university (Altonji et al., 2012; Lemieux, 2014; Altonji et al., 2016). Moreover, evidence of comparative advantage across fields of study implies that a student who might have above average earnings in one field could earn below the average in a different field (Kirkeboen et al., 2016). Even if waiting to be admitted to a particular program does not lead to higher earnings net of any costs, other studies have pointed toward substantial non-monetary returns that vary across occupations, which are linked to different fields of study (Arcidiacono, 2004; Arcidiacono et al., 2014). Taken as a whole, this literature suggests that there may be incentives for individuals to delay if it means they can enter a preferred field of study.

We build on these literatures by directly investigating the extent to which delaying is driven by admissions constraints. Relatedly, other researchers have taken advantage of a feature in admissions systems from different countries, which generates discontinuities around a threshold grade point average, to investigate the impact of being admitted into specific programs on future earnings (Kirkeboen et al., 2016; Hastings et al., 2013; Heinesen, 2018), and the impact of not being admitted into a program on fertility (Humlum et al., 2017). Such identification strategies employing GPA discontinuities generally require restricting attention to those who have applied for university. Applicants are only a subset of all delayers, and admissions constraints might influence the decision to delay even among non-applicants. Consequently, while we make use of similar variation, because our work focuses on the decision to delay our approach combines exogenous variation in admissions with structure. The structural approach further allows us to add to this literature by assessing to what extent delaying responds to different admissions incentives.

3 Danish School System

During our sample period, Denmark had 9 years of compulsory schooling. Following that, students who wished to qualify for university would enroll in an academic high school, which are called gymnasium in Danish. There were three types of high schools: ordinary, business, or technical. We focus on ordinary high school, which was the most common type. Students in these high schools could choose between two concentrations–a 'language track', with more courses in European and classical languages, or a 'math track', with more math and science courses. To enter university programs, high school graduates needed to have achieved a minimum score of 6 on a 13-point grade scheme in their qualifying exams. Some programs, particularly sciences, also required completion of specific courses, however, these prerequisites could be met by taking additional courses in university.

Students who were eligible for university would apply through a centralized application system referred to as KOT.[1] During the sample period, capacity at each university for specific programs was established by the Ministry of Education in consultation with administrators from the various institutions. The national government also legislated that a certain fraction of positions were allocated to students applying through three different pathways. Most of the capacity, 60-70 percent, was allocated to 'Group I', in which students were admitted solely on the basis of their GPA. Another 20% were allocated to applicants with work experience. The GPA of applicants applying through this channel, which was called 'Group II', was inflated by a

[1]Information regarding the admissions system in place during this period was taken from *Studie og Erhvervsvalget, Speciel del*, published by Rådet for Uddannelses- og Erhvervsvejledning in the years 1982, 1983, 1984, 1985-86, 1986-87.

factor that increased with the amount of work experience.[2] Specifically, the GPA of applicants with 9-11 months of experience was inflated by 1.09, and by 1.18 for those with at least 12 months of experience. A third class of admissions, allocated roughly 10 to 20% of the positions, was reserved for students over age 25 without a high school diploma, and students who studied outside of Denmark. This third group is not a part of our sample.

When applying, students in Group I submitted to KOT a prioritized list of programs. KOT then ranked the students according to their GPA. The Group I program capacity was allocated starting with the students with the highest GPAs. Thus, the students with the highest GPA were offered their first priority program and the likelihood of being offered a place in one's first choice program declined with GPA. If all of the positions in preferred programs had been offered to other students with higher GPAs, a student would be offered the next program on their priority list. This admissions process generated a GPA threshold in all of the programs for which there was excess demand. A similar process was followed for Group II, except that an applicant's GPA would have been adjusted according to the student's work history. Since the thresholds for both Group I and Group II were a function of relative supply and demand for each program, the exact cut-off value in future years could not be predicted by applicants. We use this source of variation in identifying the model, which we will discuss later in greater detail.

Danish universities did not charge any tuition or fees, and generous grants were available for students from lower income families. Until 1988, grant eligibility depended on parents' income for students below the age of 22. A reform implemented in that year lowered the age at which parental means-testing was required to 19.[3]

[2]This admissions class differs somewhat from the current system, first introduced in 1991, called 'Quota 2'. Under Quota 2, students are evaluated by more than just their GPA, and this can include work experience or admissions essays. In the current system, students can apply in Quota 2 and Quota 1 simultaneously.

[3]Nielsen et al. (2010) study the effect of that expansion in aid and conclude that borrowing constraints were unimportant in Denmark.

4 Data

We use data drawn from administrative registers, which cover 100% of the Danish population. In our estimating sample, we include individuals who were born in Denmark and who graduated from an 'ordinary' high school between the ages of 17 and 20. Our estimating sample includes the high-school graduating cohorts of 1981-1983. We also have data for 1984 cohort, which we reserve to assess how well our model fits the data. We further restrict the sample to students who entered one of 30 different programs at 8 major Danish universities within 2 years of their terminal high school program and who graduated from university with 5-year Candidature degrees within 10 years.[4] Table 1 lists each of the sample programs categorized by university and field of study.[5] There are five broad fields of study, which are Humanities, Natural Sciences, Social Sciences, Engineering, and Medicine. We define the student's field of study according to the program they entered first.[6]

For our sample, we combine data from four different administrative registers with university admissions and funding data so that we observe a number of important schooling and labour market outcomes. First, from the Danish Student Register, we observe, annually, enrollment and any credentials obtained from specific university programs and institutions. For individuals who graduated from ordinary high schools, we observe the average high school grade which was used to qualify for university. In the second register, the Integrated Database for Labour Market Research (IDA), we observe annual earnings, and other labour market outcomes. This register is used to construct our lifetime earnings measures, as well as earnings during schooling and years of delay. Third, we use a demographic register, which links the individuals to their

[4]These restrictions allow us to observe ten post-schooling years of income.

[5]The sample programs represent 85% of all the fixed enrollment quotas at the 8 universities during the sample period.

[6]Students who might want to switch programs would be required to apply again through the normal admissions process. In our data, 94% of the students graduate with a Candidature in the same field of study they first entered.

parents, to construct age, sex, geographic, and family background variables. Finally, from an income register, we obtain annual records of the amount of student financial aid received.

We collected the admissions data from archival reports produced by KOT. The reports were published annually in July and contain information on the total number of places available in each program across Denmark, the number of applicants, the GPA threshold for each admissions class and the number of positions still available. We use data from the reports for 1981 to 1986. Unfortunately, the GPA thresholds are missing from the 1987 archived report. This missing data has restricted our sample period.[7] We also use data collected from annual publications of the "Finance Act", which specifies funding levels for universities broken down by the faculty. Specifically, we use the projected student-to-teacher ratios upon which grant allocations were based. We summarize the sample data in Table 2.

5 Who delays?

Before presenting the structural model, we begin by examining which, if any, individual characteristics are associated with delaying university. In Table 3, we report estimates from OLS regressions where the dependent variable is an indicator for whether the individual delayed by one or two years. The regression in the first column includes measures of family background, age at high school graduation, and the local youth unemployment rate.[8] These results suggest that students whose mothers have lower levels of education are less likely to delay. Father's education is not statistically related to delay, with the exception that students for whom there is no data on father's education delay less often. The local youth unemployment rate in the year of high school graduation is positively correlated with delaying, however, the effect size

[7]Another reason for using these earlier years is because program categories in the KOT were consistent across these years. After 1987, many programs were added and split.

[8]All specifications include controls for region of residence in last year of high school and high school graduating cohort.

is small and becomes negative and statistically insignificant when we control for the student's sex.[9]

In columns (2) to (4), we sequentially add an indicator for the students' sex, their high school grade point average (GPA), and an indicator for whether they completed the Mathematics track in high school, respectively. Each of these characteristics are strong predictors of delay. In the specification in column 4, women are roughly 14 percentage points more likely to delay than men. This is despite the fact that some fraction of the men delaying university may have been participating in compulsory military service.[10] Students who pursue the mathematics track (as opposed to the language track) are almost 17 percentage points less likely to delay university. Individuals with higher high school grades are also less likely to delay. On average, a one standard deviation difference in high school GPA, which is 0.8, is related to a 6.4 percentage point difference in the likelihood of delaying.

The relationship we observe between delaying and grades is consistent with the view that some students might delay because they hope to be admitted to a preferred university program. Furthermore, the likelihood of having delayed entrance into university varies substantially depending on the field of study entered. Across the whole sample, 42% enter university after a delay of one or two years. Students who enter the Social and Natural Sciences, delay at rates close to the average. Specifically, these rates are 46 and 42%, respectively. Humanities graduates are by far the most likely to delay entrance. Indeed, only one third of Humanities students entered without delay. This behaviour is in stark contrast to Engineering graduates, among whom 75% enter university directly. Roughly 45% of Medical students delay, which is more

[9]Sievertsen (2016) finds that local unemployment rates predict the timing of enrollment in any form of post-secondary schooling, but his results suggest that completion of university specifically is not affected. He does not present any evidence about enrollment in university.

[10]During the sample period, military service was compulsory for a fraction of 18 year-old men selected by lottery. In 1979, 27% of all 18 year-old men were conscripted while in 1989, 24% were conscripted (Sorensen, 2000). We are unfortunately unable to explore this further because military service is not well observed in the Danish registers that we are using.

often than average, but less often than Humanities students. Because of the stark contrast in the propensities to delay across fields of study, we model the decision to delay jointly with the decision to enter a particular field. The structure of the model allows us to uncover the extent to which the decision to delay is a result of admissions restrictions.

6 Model

In this section, we describe the dynamic three-period model that we use to investigate how the timing of university enrollment might change under different admissions policies. In the model, individuals choose between delaying or entering one of 30 different university programs. Entering a program is an absorbing state and students delay at most two years. A student can only enter a program for which they are qualified, meaning that their own high school GPA is above a program- and year-specific threshold GPA in the relevant admissions class. Students entering programs directly from high school apply through the Group I admissions class. After delaying, students apply through Group II, and have their GPA inflated by a factor that depends on their years of delay.[11] For most students, delaying changes the set of programs for which they are eligible.[12]

6.1 Utility of schooling and delaying

It is useful to think of individual i's indirect utility from entering a particular program p, following g years of delay, as occurring in two separate periods, which are during and following schooling. Indirect utility in the post-schooling period is the present value of lifetime earnings

[11] We do not observe hours worked, and so we assume that students who delay for one year are eligible for the 1.09 GPA multiplier, and students who delay by two are eligible for the 1.18 multiplier.

[12] After two years of delay, the Group II threshold is always lower than the Group I threshold. However, after only one year of delay, because the GPA multiplier is smaller, in some high excess demand programs the Group II threshold is higher than that in the Group I admissions class.

plus a random shock:[13]

$$\upsilon^E_{ipg} = PV\ earn_{ipg} + \epsilon^E_{ipg} \tag{1}$$

Indirect utility, while in school, depends on how long it takes to complete the program (dur_{ipg}), earnings while in school ($earn_{ipg}$), and student financial aid (SFA_{ig}):

$$\upsilon^S_{ipfg} = \alpha_f + \alpha_x X_{ipf} + earn_{ipg} + SFA_{ig} + \alpha_d dur_{ipg} + \epsilon^S_{ipg} \tag{2}$$

Additionally, utility depends on the characteristics of the program (X_{ipf}), some of which are common across the field of study, indexed by f. Included among these characteristics are indicators for whether one's mother and father hold a candidature in the program's field of study and indicators for whether the program is in the same city or region in which the students lived during their last year of high school. The final characteristic in this vector is the ratio of students to academic staff, which varies by university, as well as field of study and cohort.

We also allow utility during school to depend on whether the field of study a student enters matches their sex and high school track, where 'matching' means the majority of the students have the same sex or high school track. Two faculties, Humanities and Medicine, are dominated by women, while the other three are dominated by men. This specification allows the utility of entering a male or female dominated field to differ across men and women. With respect to high school concentration, Natural Science, Engineering, and Medicine are coded as math-track fields of study, and the others are language-track.[14] The indicator for whether a student's high

[13]In the data, we measure lifetime earnings in the chosen program, given the chosen years of delay using an individuals' actual earnings for 10 post-schooling years and imputed earnings projected out to age 60. The imputed earnings are based on growth rates estimated in data from previous cohorts. More details about the construction of the lifetime earnings and student aid are available in supplemental appendix A. Throughout, we use an annual discount rate of 4%.

[14]The characteristic of a program as being dominated by either sex or high school concentration is quite stable over time. By 2010, only Social Science had changed in these two dimensions. In that year, men and

school track matches their field of study can capture any additional effort that is required when, for example, a language-track student enters Natural Sciences. Finally, utility while in school includes a field-of-study specific intercept α_f, and the idiosyncratic randomness associated with schooling preferences are reflected in ϵ^S_{ipg}.

Rather than entering a program, students can delay for a year. The indirect utility from delaying university by one year, conditional on having delayed by g years is:

$$\upsilon^G_{ig} = \gamma_{sg} + \gamma_{hg} + \gamma_c + \gamma_u unemp_{ig} + \gamma_a age_{ig} + earn_{ig} + \epsilon^G_{ig} \tag{3}$$

To capture differences in the nature of work or other activities pursued during a gap year, the value of delaying depends on the students' sex (γ_{sg}) and high school track (γ_{hg}). For example, men might be doing military service. Delaying also depends on the high school graduating cohort (γ_c), students' current age, their earnings during the year of delay, the local youth unemployment rate, and a random component (ϵ^G_{ig}).

6.2 Solution

The problem of jointly choosing when and which program to enter is solved by backward induction. In the final period, students compare the value of all the programs for which they are eligible and enter the program with the highest value. In the preceding periods, students compare the value of delaying by one year to entering the highest-valued program for which they are qualified.

In each period, when a student must choose between entering a program or delaying, we assume that the current-period preference shocks for schooling and delaying are known. We further make the simplifying assumption that students can observe all the current-period threshold

women entered this field with the same frequency and students were drawn from a variety of high school concentrations. As such, within the cohorts in our sample, an individual students' choice will not affect how a field is characterized along these two dimensions.

GPAs and thus know before committing for which programs they are eligible.[15] In contrast, a student takes expectations over earnings, time to completion and student financial aid. Expected earnings, whether during delay, or during and after schooling, are conditional on years of delay, age at high school graduation, sex, high school grades and concentration, and cohort. Additionally, expected earnings during and post schooling vary by program. Similarly, students' expected time to completion is conditional on their program, years of delay, sex, and high school grades and track. Expected student financial aid depends on the students' age at high school graduation, cohort, and the expected study duration. [16]

If we assume the lifetime earnings shock, ϵ^E_{ipg} from (1), is drawn from an extreme value distribution, with location equal to zero and a scale of τ, then the value of entering program p after g years of delay is:[17]

$$V^S_{ipg} = Q_{ipg}\left(\alpha_f + \alpha_x X_{ipf} + \mathbb{E}\left[earn\right]_{ipg} + \mathbb{E}\left[SFA\right]_{ig} + \alpha_d \mathbb{E}\left[dur\right]_{ipg} + \epsilon^S_{ipg} + \rho\left(\mathbb{E}\left[PV\ earn_{ipg}\right] + \tau\lambda\right)\right) \tag{4}$$

Where $Q_{ipg} = 1$ when a student is qualified for a program, and zero otherwise, ρ discounts future earnings by the expected duration of schooling, and $\lambda = 0.577$ is Euler's constant. Given this definition of the value of schooling, the solution in the final period is simply to enter the program p such that $V^S_{ip2} > V^S_{ir2}$ for all $r \neq p$.

In periods 0 and 1, students can choose to delay rather than enter a program. The value of delaying is the sum of current-period utility and the expected continuation value:

[15] Although thresholds are unknown in June when students apply, we make this assumption because a) the application system was strategy proof, such that students had no incentive to misrepresent their true preferences in their rankings, b) before programs began, in September, the GPA cutoffs and the number of places still available were published. Thus, students who had not received an offer could choose one of the available programs before committing to delaying.

[16] In the data, we estimate these conditional expectations with conditional sample means.

[17] The expected values have individual subscripts to indicate that the expectations are conditional on the individual characteristics described in the previous paragraph.

$$
\begin{aligned}
V_{ig}^{G} &= \gamma_{sg} + \gamma_{hg} + unemp_{ig} + \gamma_a age_{ig} + \mathbb{E}\left[earn\right]_{ig} + \epsilon_{ig}^{G} \\
&+ \beta \mathbb{E}\left[\max\left(V_{ig+1}^{G}, V_{i1g+1}^{S}, \ldots, V_{ipg+1}^{S}, \ldots V_{i30g+1}^{S}\right)\right] \qquad (5)
\end{aligned}
$$

Solving for $\mathbb{E}\left[\max\left(V_{ig+1}^{G}, V_{i1g+1}^{S}, \ldots, V_{ipg+1}^{S}, \ldots V_{i30g+1}^{S}\right)\right]$ involves taking expectations over the unknown future preference shocks, ϵ_{ig+1}^{G} and all of the ϵ_{ipg+1}^{S}, and also forecasting the probability of qualifying for a program under the Group II admission class. Future, Group II GPA thresholds are unknown but we assume that students' believe these thresholds ($THGPA_{pg}^{II}$) follow a random walk: $THGPA_{pg}^{II} = THGPA_{pg-1}^{II} + \eta_{pg}$

Additionally, we assume that the deviation from last periods' threshold, η_{pg}, is uniformly distributed with a support of $\left\{-\sigma_{\eta_f}, \sigma_{\eta_f}\right\}$. We do not estimate σ_{η_f}, but instead use two standard deviations, within each field of study, of the changes in group two thresholds observed in the data during the sample period. Specifically, $\sigma_{\eta_f} = \{.6, .4, .7, 1, .3\}$ for Humanities, Natural Sciences, Social Sciences, Engineering, and Medicine, respectively.

Since a student, who has delayed, is qualified when their own GPA, multiplied by the relevant Group II multiplier (m_g), is above the threshold, a student believes the probability of being qualified in the next period is:

$$
\mathbb{E}\left[Q_{ipg} | GPA_i, m_g, g > 0\right] = \begin{cases} 0 & \text{if } GPA_i * m_g < THGPA_{pg-1}^{II} - \sigma_{\eta_f} \\ \frac{\left(GPA_i * m_g - THGPA_{pg-1}^{II}\right) + \sigma_{\eta_f}}{2\sigma_{\eta_f}} & \text{if } -\sigma_{\eta_f} \leq GPA_i * m_g - THGPA_{pg-1}^{II} > \sigma_{\eta_f} \\ 1 & \text{if } GPA_i * m_g \geq THGPA_{pg-1}^{II} + \sigma_{\eta_f} \end{cases}
$$

This specification treats changes in the threshold as unanticipated and conditionally independent of individual behaviour. It further allows us to greatly reduce the dimensionality of the problem, which if unconstrained would involve integrating over 2^{30} choice sets. Essentially, if a student's GPA is more than σ_{η_f} above or below the threshold this period, she assigns a probability of being qualified next period of 1 or zero, respectively.

Finally, we fully characterize the solution by assuming that the preference shocks are distributed as Extreme Value (Type 1), with a location of zero and scale of τ. Under those assumptions the Emax has a closed form solution (McFadden, 1977). If a student is qualified with probability one for all programs in the next period, the Emax in (5) is:

$$\mathbb{E}\left[\max\left(V^G_{ig+1}, V^S_{i1g+1}, \ldots, V^S_{i30g+1}\right)|P_{ipg} = 1 \ \ \forall\, p\right] = \tau \ln\left[\exp\left(\frac{1}{\tau}\bar{V}^G_{ig+1}\right) + \sum_p \exp\left(\frac{1}{\tau}\bar{V}^S_{ipg+1}\right)\right] + \tau\lambda$$

where $P_{ipg} = \mathbb{E}\left[Q_{ipg}|GPA_i\right]$.

However, for most students $P_{ipg} < 1$ for some subset of the programs. When that is the case, the Emax is a weighted average of the expected maximum value from all of the possible combinations of programs for which a student might be qualified next period. The weights are the probabilities associated with being qualified for each combination of programs.[18]

6.3 Estimation and Identification

Because the solution to the model has a closed form, we use Maximum Likelihood to estimate the parameters of the model. In total, there are 21 parameters to estimate. The observed choices will identify, up to scale, the coefficients in the utility equations. The scale of the preference shocks, τ, will fit differences in enrollment rates that are unexplained by the average choice-specific utilities, including differences in lifetime earnings.

The variation in GPA thresholds, in both admissions groups, provides an important source of exogenous variation. Although we do not observe students' rankings, we do know for which programs they are eligible. When a student delays, their choice reveals that the value of delay

[18] An example of such a weighted average Emax is given in supplemental appendix B.

must be larger than the value of any of the programs for which the individual is qualified. The unpredictable fluctuations in the thresholds generates useful variation both within and across cohorts in the set of programs for which a student is eligible. Within a cohort, students with GPAs just above or below a threshold will face a different set of options, despite having similar grades. Because the thresholds vary year by year, program eligibility will vary across students with identical GPAs because of their high school graduating cohort. In Figure 1, we show the changes in the thresholds for each program in Groups I and II. An additional table summarizing the thresholds is available in supplemental appendix C.

7 Results

Once we have estimated the parameters, the structural model allows us to manipulate the policy environment, and, using simulated data and shocks, investigate the distribution of choices under counterfactual admissions constraints. Because they are not of direct interest, we report the estimated parameters in supplemental appendix D. In this section, we begin by evaluating the model by demonstrating how well it can predict the distribution of delay both in and out of sample. Following that discussion, we present the results from the counterfactual experiments.

In assessing the fit of the model, our main focus is on how well our model can predict the distribution of delay. Because the reduced form estimates suggest that students' sex and high school track are important predictors of delaying, we also report the extent to which we can match distributions within those subgroups. In Figure 2, we compare the distribution of delay in data to simulated distributions. We do this for the sample period, 1981-1983, and for the 1984 cohort which was not used in the estimation. The simulated distributions were constructed by randomly drawing samples and a set of preference shocks 100 times and then determining the distribution of choices conditional on those shocks.[19]

[19]Tables with the simulated distributions and standard errors are reported in supplemental appendix E. That

As one would expect the within-sample simulated distribution of delay matches the sample data fairly closely. A better gauge of the model's fit is the extent to which the simulations match the out-of-sample distributions, particularly when the distributions change between the 1981-1983 sample and the 1984 data. The fraction of students entering university directly from high school is 3 percentage points lower in the 1984 data when compared to the 1981-1983 sample data. In our simulated distributions, we match, within a percentage point, both the level of direct entry and the change across cohorts. Similarly, within the male and female subgroups, and for those who have completed the Math concentration in high school, our model can match changes in the propensity to delay reasonably well. For the subgroup of students who followed the Language track in high school, our model over-predicts the propensity to delay both in and out of sample. While this sub-group does have a higher than average propensity to delay in the data, they represent only 22% of the sample. Overall, our assessment is that the model fits the data both in and out of sample sufficiently well to analyze our counterfactual experiments.

7.1 Delaying under Counterfactual Admissions Constraints

The main purpose of our counterfactual experiments is to analyze the extent to which individuals alter the timing of entry into university because they are constrained from entering their preferred program. The policy experiments also help us understand more deeply the ways in which the incentives generated by the admissions policies affect net and gross flows across delay and field of study.

Using the parameters estimated in the model, we perform counterfactual experiments that alter the GPA thresholds faced by students. We randomly draw a sample of students and their preference shocks 100 times, impose the threshold changes, and then summarize the resulting distributions of years of delay and fields of study.

appendix also includes analogous figures for how well our model fits the distribution of field of study.

The counterfactuals are intended to reveal how the existing stock of graduates of Candidatures would respond to changes in the admissions constraints, holding constant the direct utility of delaying and the utility of entering a field of study following any given years of delay. With this in mind, in each of the experiments, we allow the number of positions available in all programs to expand to meet demand among students qualified under the particular set of GPA thresholds. We also hold expected life-time earnings constant for each choice pathway. Essentially, we do not allow for any general equilibrium effects stemming from, for example, changes in the relative number of doctors. As such, these experiments are not informative about broader long-run labour market impacts. Since, in our model, we condition on completing a Candidature, our counterfactual experiments do not allow for new enrollments or new graduates. Because of this, each experiment weakly expands the set of choices available to each student. This is important because if we restricted the choice set, some students might prefer 'no university' to the constrained set of choices.

In Table 4, we show the distributions of delay that are generated by each of three different experiments, along with the 'baseline' case, which refers to the simulated results using the actual GPA thresholds from 1981-1983. The first experiment, called 'free entry', eliminates the GPA thresholds from all programs in all years. This is essentially completely open admissions for high school graduates with a GPA of at least 6. Moreover, this experiment eliminates any risk associated with fluctuations in future GPA thresholds. In the free-entry experiment students reveal their wholly unconstrained choices in terms of both the timing of entry and the field of study entered.

Compared to the baseline, the percentage of students who enter university directly from high school increases from 57.22 to 63.06%. This 5.84 percentage point increase is generated by roughly equal reductions in the fractions delaying by one or two years. These shifts in the distribution of delay are the net effect of two different and counteracting incentives that are generated by eliminating both the admissions constraints and the risk associated with future GPA thresholds.

In the baseline policy environment, there is, potentially, a set of students who delay because their GPA is below the threshold of their preferred program in a given year. The elimination of thresholds in the free-entry experiment, holding all else constant, should induce these students to reduce their years of delay. There is a less obvious and countervailing effect that could occur because there is no risk associated with future GPA thresholds in the free-entry experiment. There might be some students in the baseline environment who would prefer to delay to a future period, but enter university in the current period because of the presence of future risk. The elimination of risk would tend to encourage these students to delay more often or for more years.

To disentangle these two effects and to quantify their magnitudes, we calculate the gross flows from the years of delay in the baseline to that in the free-entry environment. These flows are reported in Table 5, where the rows and columns correspond to the baseline and free-entry environments, respectively. The number in each cell represents a fraction of the entire simulated sample; as such, the sum of all cells in the table is one.

The sum along the diagonal of Table 5, which is 89.26%, represents the fraction of students who, relative to the baseline, do not alter their years of delay in the free-entry experiment. A revealed-preference argument suggests that these students are unconstrained, in terms of the timing of entry, in the baseline admissions environment. When all options are available, the students choose the same years of delay as they do in the baseline, implying that the relevant baseline constraints do not bind for this group of students.

The fraction of the simulated sample who decrease their years of delay in the free-entry experiment is found by summing the lower off-diagonal cells in Table 5. These cells sum to 8.85% of the simulated sample, representing 20.69% of all baseline delayers. From revealedpreferences, and because we hold constant all other modelled facets of utility, we can infer that these students delay because they could not enter a preferred program in an earlier period. Among the students who enter more quickly in the unconstrained and risk-free experiment, most enter university directly from high school. Specifically, 7.29% of the simulated sample are baseline delayers who enter university after zero years of delay in the free-entry experiment, and 1.56% reduce their delay from two years to one.

The sum of the upper off-diagonal cells reports the opposite effect of the free-entry experiment, relative to baseline. That sum reveals that 1.87% of the simulated sample increase their years of delay. This effect is driven by the elimination of future risk in the free-entry experiment. The free entry experiment demonstrates that for these students, in the absence of risk, delaying and entering a program in a future period dominates entering any program in the current period. These students' baseline choices are available in the free-entry experiment, yet those options are not chosen. This suggests that, in the baseline, for these students the expected value of a risky future choice combined with the direct value of delaying is lower than the utility from the best current option.

When comparing the baseline to unconstrained and risk-free admissions, the 5.84 percentage point net increase in direct entry results from the 7.29% gross increase in the fraction with zero years of delay minus the 1.45% who flow from zero years of delay to at least one year of delay. Thus, in the 1981-1983 sample period, the dominant effect of the admissions system on the timing of university enrollment is to increase years of delay. Overall, however, for the vast majority, more than 89%, the admissions constraints has no effect on when students enter university.

The next experiment, reported in the third column of Table 4, combines free entry after zero years of delay with the baseline environment after at least one year of delay. This counterfactual is labeled "free entry with no delay", and we will call it the "no-delay" experiment for ease of exposition. In this experiment, students can enter any program if they enter directly from high school; if they delay then they face the usual Group II GPA thresholds, and the risk associated with fluctuations in those thresholds. This experiment focuses the admissions incentives on entering with zero years of delay, and, as a side effect, shuts down the free-entry incentive to delay by one year among those who enter directly in the baseline.

Comparing the fraction of the simulated sample that enter university directly from high school in the baseline to that in the no-delay experiment reveals a net increase of 8.01 percentage points. Within the sample period, this is largest effect on direct entry that such policy experiments might induce.

Using the free-entry experiment as a benchmark with which to compare the no-delay experiment contrasts an unconstrained and risk-free distribution of choices to one in which direct entry is incentivized. The government might want to encourage students to enter directly, even if that is not their unconstrained choice, if, for example, delaying reduces tax revenues. In this comparison, the net increase in direct entry is 2.17%.

In Table 6, we report the gross flows from years of delay in the free-entry experiment to the no-delay experiment. Again, the cells sum to one. Since in both experiments students are free to enter any program they choose after zero years of delay, and because all other aspects of utility are held constant, all of the students who enter directly in the free-entry experiment do the same in the no-delay experiment. This group represents 63% of the simulated sample.

The percentage of the sample that was induced, from their free-entry choice, by the no-delay experiment to reduce their years of delay to zero is only 2.18%. That this effect is so small suggests that among those who, in the baseline environment, delay because their GPA is below the threshold of a preferred program, most would, in the absence admissions restrictions, prefer to enter directly.

In the no-delay experiment, given that a student has delayed by one year, the constraints on the decision to delay a second year are identical to the baseline. Thus, along that margin, Table 6 reveals movements similar to the comparison of baseline to free-entry. Specifically, 1.5% of the sample delay by two years, rather than one year because of the Group II GPA thresholds. In the other direction, only a tiny fraction 0.41% delay by one year rather than two years.

Because both the free-entry and no-delay experiments allow students to enter any program, the changes in the distribution of delay may result from substantial shifts in the distribution of field of study. In Table 7, we report the resulting distributions of field of study for the baseline, the free-entry experiment, and a third counterfactual, which we will discuss shortly. Relative to the baseline, in the free-entry experiment, the net flow is primarily into medicine. Although the shares in all other fields contract, the largest reduction is in Engineering.

To further investigate this net difference in the field of study, and how it is related to the changes in delay, we calculate the gross flows across the joint distribution of delay and fields. In the joint distribution, there are 15 outcomes, and in Table 8 we report the fraction of the simulated sample flowing from each of the outcomes in baseline to each outcome in the free-entry experiment.

The diagonal in this table, which is shaded dark grey, represents the sample who did not change their field of study or their years of delay in the free-entry experiment. The sum of those cells totals 77.77%. Among those who did change their choice, there are three different types of movement. First, students might alter their timing of entry but remain in the same field of study. These outcomes are shaded light grey. Less than one percent of the sample increase their years of delay and 2.05% enter after fewer years of delay, while remaining in their baseline field. This latter group of students are primarily those who enter the high excess-demand fields of Medicine and Social Science.

The second type of movement involves changing the field of study without altering the timing of entry. More than 11% of the sample make such a change.[20] From the point of view of a policy maker hoping to encourage direct entry this would be the least desirable behavioural response. Indeed, most of this movement, 8.17% of the sample, is generated by flows into Medicine.

Finally, the third type of movement, made by 8.04% of the sample, involves shifts in both field and years of delay. Almost half of this group is students who delay in the baseline and then enter Medicine without delay in the free-entry experiment. Although students from all other baseline fields flow into Medicine, the largest shares come from the baseline fields of Engineering and Social Sciences.

As we noted previously, 8.85% of the simulated sample reduce their years in the free-entry experiment relative to baseline. Of those students, 56.2%, which is roughly 5% of the whole sample, switch from their baseline field into Medicine. Because such a large fraction of the reduction in delay is driven by the flow into Medicine, we perform a third experiment that removes the admissions constraints in all years from all programs *except* Medicine. We call this experiment "free entry, except Medicine."

The distribution of delay in this counterfactual is reported in the fourth column of Table 4 and the distribution of fields is reported in the third column of Table 7. When students can freely enter any program except Medicine, we observe a distribution of delay that is very similar to that in the free-entry experiment. Similarly, the free-entry-except-Medicine experiment increases direct entry by 6.26 percentage points relative to baseline. In contrast, however, the distribution of fields in the free-entry-except-Medicine experiment is relatively close to the baseline distribution. The share in Social Sciences increases by 3.17 percentages points, drawing mostly from Engineering.

From Table 9, we can learn why this experiment generates a net reduction in delay that

[20]In the table, this figure comes from summing the off-diagonal cells in the three 5 by 5 diagonal blocks.

is similar to the free-entry experiment but does not generate the same shift in the fields of study. This table reports the gross flows from the baseline to the free-entry-except-Medicine experiment. The percentage of students who reduce their baseline years of delay is 7.91%. This is less than one percentage point smaller than the analogous figure in the free-entry experiment. This follows, in part, because very few baseline Medical students reduce their years of delay in the free-entry experiment.

The key difference between the gross flows in the free-entry and free-entry-except-Medicine experiments is the movement across fields without changing the timing of entry. Recall that in the free-entry experiment, the fraction of the simulated sample making this type of shift was 11.5%. In the free-entry-except-Medicine experiment that figure is 3.98%. Thus, the free-entry-except-Medicine essentially shuts down the "windfall" behaviour in which students enter Medicine without reducing delay. Although, generally our findings imply that relaxing admissions restrictions will not dramatically reduce delay, this particular finding does suggest in designing such policies, it is important to consider their impact on high excess-demand programs.

8 Conclusion

We investigate the extent to which the common practice of delaying university among Danish students is affected by admissions policies. This question is motivated by the observation that the propensity to delay varies substantially across field of study. We study the admissions policies active in the early 1980's. The policies from this period share many key features with current policies in Denmark and other Nordic countries. In particular, the minimum GPAs required for admission to some programs change unpredictably due to excess demand and fixed enrollment quotas.

We model this policy environment using a dynamic discrete choice model in which high school graduates choose whether to enter a program into which they have been admitted in that period or to delay to the next period. The set of program choices in future periods fluctuate unpredictably, and this generates an incentive for some to delay and conversely for other to enter directly. In the context of the random GPA thresholds, our use of structure has two advantages. First, we exploit the exogenous changes, within and between cohorts, in minimum GPA thresholds to help identify the model. Second, the structure allows us to quantify the gross effects of the two countervailing incentives.

We find that the incentive to delay dominates the incentive to enter directly. However, our simulated policy experiments also suggest that the percentage of high school graduates delaying university would only fall by 5.8 percentage points in a completely open admissions system. This is primarily because, among the students who delay, just 1 in 5 do so because of admissions restrictions.

In this type of admissions system, the minimum GPA restrictions always bind for some students because the restriction only exists when there is excess demand. As such, our results imply that although students are constrained by the fixed supply of positions, not all of those students are willing to delay because of the constraints.

For policy makers interested in accelerating young people's entry into the full-time labour market, our results suggest that there is limited scope to substantially reduce the amount of delaying with programs that give students who apply directly from high school advantages in admissions. Although we do not study this issue directly, financial incentives, which have been shown to reduce the time taken to complete a degree (Garibaldi et al., 2012; Gunnes et al., 2013), may prove more effective.

References

Altonji, J.G., P. Arcidiacono, and A. Maurel, *The Analysis of Field Choice in College and Graduate School*, Vol. 5 of *Handbook of the Economics of Education*, Elsevier, June

Altonji, Joseph G., Erica Blom, and Costas Meghir, "Heterogeneity in Human Capital Investments: High School Curriculum, College Major, and Careers," *Annual Review of Economics*, 07 2012, *4* (1), 185–223.

Arcidiacono, Peter, "Ability sorting and the returns to college major," *Journal of Econometrics*, 2004, *121* (1-2), 343–375.

_ **, V. Joseph Hotz, Arnaud Maurel, and Teresa Romano**, "Recovering Ex Ante Returns and Preferences for Occupations using Subjective Expectations Data," NBER Working Papers 20626, National Bureau of Economic Research, Inc October 2014.

Crawford, Claire and Jonathan Cribb, "Gap year takers: uptake, trends and long term outcomes," Technical Report, Institute for Fiscal Studies through the Centre for Analysis of Youth Transitions (CAYT) 2012.

Ferrer, Ana M. and Alicia Menendez, "The Puzzling Effects of Delaying Schooling on Canadian Wages," *Canadian Public Policy*, September 2014, *40* (3), 197–208.

Garibaldi, Pietro, Francesco Giavazzi, Andrea Ichino, and Enrico Rettore, "College Cost and Time to Complete a Degree: Evidence from Tuition Discontinuities," *The Review of Economics and Statistics*, August 2012, *94* (3), 699–711.

Gunnes, Trude, Lars J. Kirkeben, and Marte Rnning, "Financial incentives and study duration in higher education," *Labour Economics*, 2013, *25* (C), 1–11.

Hastings, Justine S., Christopher A. Neilson, and Seth D. Zimmerman, "Are Some Degrees Worth More than Others? Evidence from college admission cutoffs in Chile," NBER Working Papers 19241, National Bureau of Economic Research, Inc July 2013.

Hauschildt, Kristina, Christoph Gwosć, Nicolai Netz, and Shweta Mishra, *Social and Economic Conditions of Student Life in Europe. Synopsis of indicators. Final report. Eurostudent IV 2012 2015.*, Bielefeld: W. Bertelsmann Verlag, 2015.

Heinesen, Eskil, "Admission to higher education programmes and student educational outcomes and earnings–Evidence from Denmark," *Economics of Education Review*, 2018, *63* (C), 1–19.

Holmlund, Bertil, Qian Liu, and Oskar Nordström Skans, "Mind the gap? Estimating the effects of postponing higher education," *Oxford Economic Papers*, October 2008, *60* (4), 683–710.

Humlum, Maria Knoth, Jannie H.G. Kristoffersen, and Rune Vejlin, "College admissions decisions, educational outcomes, and family formation," *Labour Economics*, 2017, *48* (C), 215–230.

Kirkeboen, Lars J., Edwin Leuven, and Magne Mogstad, "Field of Study, Earnings, and Self-Selection," *The Quarterly Journal of Economics*, 2016, *131* (3), 1057–1111.

Lemieux, Thomas, "Occupations, fields of study and returns to education," *Canadian Journal of Economics*, November 2014, *47* (4), 1047–1077.

Light, Audrey, "The Effects of Interrupted Schooling on Wages," *The Journal of Human Resources*, 1995, *30* (3), pp. 472–502.

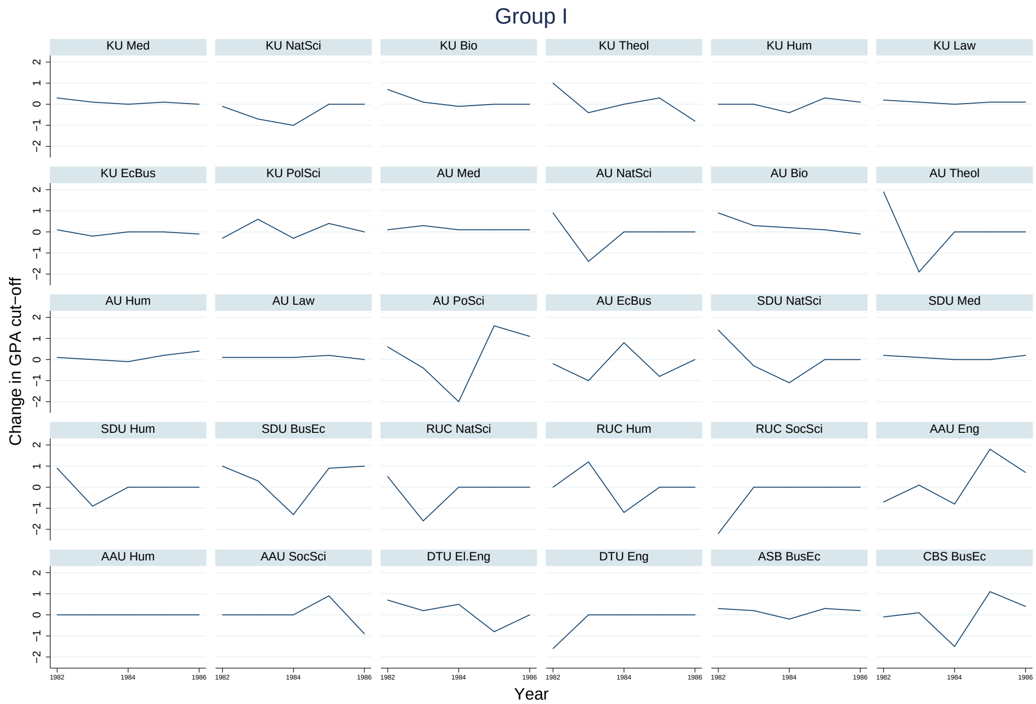
McFadden, Daniel L., "Modelling the Choice of Residential Location," Cowles Foundation Discussion Papers 477, Cowles Foundation for Research in Economics, Yale University 1977.

Monks, James, "The impact of college timing on earnings," *Economics of Education Review*, October 1997, *16* (4), 419–423.

Nielsen, Helena Skyt, Torben Sørensen, and Christopher Taber, "Estimating the Effect of Student Aid on College Enrollment: Evidence from a Government Grant Policy Reform," *American Economic Journal: Economic Policy*, May 2010, *2* (2), 185–215.

Sievertsen, Hans Henrik, "Local unemployment and the timing of post-secondary schooling," *Economics of Education Review*, 2016, *50*, 17 – 28.

Sorensen, Henning, "Conscription in Scandinavia During the Last Quarter Century: Developments and Arguments," *Armed Forces & Society*, Winter 2000, *26* (2), 313–334.



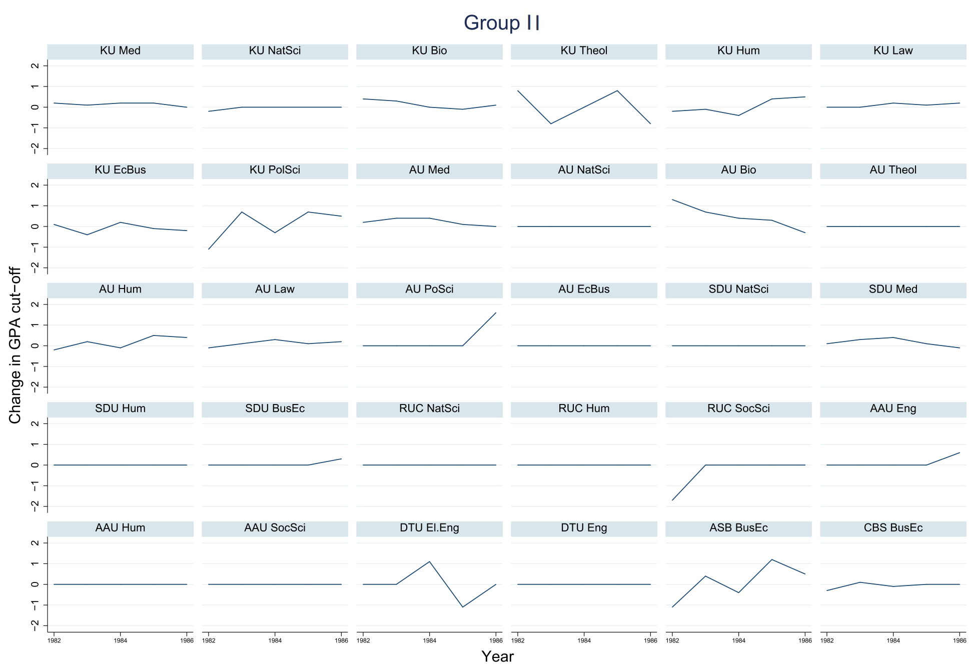


Figure 1: Changes in Minimum GPA Thresholds

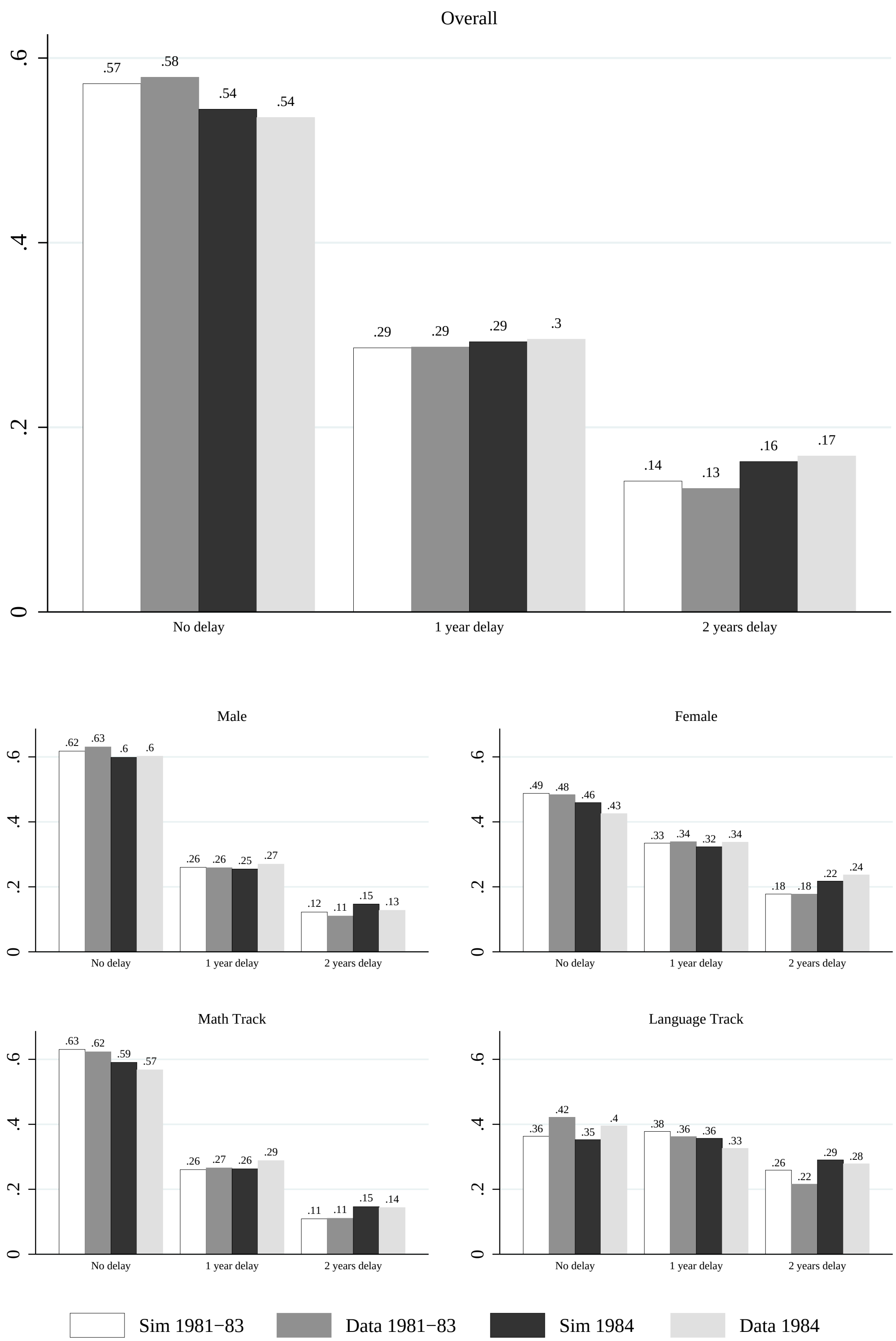


Figure 2: Model Fit: Distribution of Delay

Notes: Model estimated using data from 1981-1983. Data used to assess fit from 1984.

Table 1: Sample Programs, by Field of Study, and Universities

Universities	Humanites	Natural Sciences	Social Sciences	Engineering	Medicine
	Faculties				
University of Copenhagen (KU)	Theology Humanities	Biology Other natural sciences	Law Business/Economics Political Science		Medicine
Aarhus University (AU)	Theology Humanities	Biology Other natural sciences	Law Business/Economics Political Science		Medicine
University of Southern Denmark (SDU)	Humanities	Natural Sciences	Business/Economics		Medicine
Roskilde University (RU)	Humanities	Natural Sciences	Social Sciences		
Aalborg University (AAU)	Humanities		Social Sciences	Engineering	
Danish Technical University (DTU)				Engineering	
Aarhus Business School (ABS)			Business/Economics		
Copenhagen Business School (CBS)			Business/Economics		

Table 2: Sample Means (Standard Errors For Continuous Variables in Parenthesis)

	Total	**Years of Delay** Zero	One	Two
Years of Delay				
Zero years	0.579			
One year	0.287			
Two years	0.134			
High school exam grades	8.877	8.950	8.823	8.674
	(0.010)	(0.013)	(0.019)	(0.025)
Female	0.350	0.292	0.414	0.465
Age at high school graduation	18.600	18.578	18.645	18.595
	(0.008)	(0.011)	(0.016)	(0.022)
High School Concentration				
Language	0.219	0.159	0.276	0.353
Mathematics	0.781	0.841	0.724	0.647
Years taken to complete degree	7.019	6.911	7.141	7.227
	(0.018)	(0.023)	(0.035)	(0.051)
Earnings and Student Aid, all in millions of real (Year 2000) DKK				
Discounted Post-Schooling Earnings	6.776	7.050	6.501	6.180
	(0.052)	(0.068)	(0.096)	(0.131)
Discounted Student Financial Aid	0.080	0.046	0.103	0.174
	(0.001)	(0.001)	(0.002)	(0.002)
Discounted Earnings During Degree	0.405	0.393	0.415	0.441
	(0.004)	(0.005)	(0.006)	(0.011)
Earnings During First Year of Delay			0.051	0.047
			(0.001)	(0.001)
Earnings During Second Year of Delay				0.104
				(0.002)
Sample Size	6,770	3,921	1,943	906

Table 3: Characteristics Associated With Delaying University (Standard Errors in Parenthesis)

Average high school exam grades		-0.068***	-0.076***	-0.082***
		(0.008)	(0.007)	(0.007)
Female			0.173***	0.123***
			(0.015)	(0.015)
High school track - Math				-0.171***
				(0.015)
% youth unemployed in city	0.008***	0.009***	-0.001	-0.001
	(0.001)	(0.001)	(0.002)	(0.002)
Age at high school graduate –Reference group Age 17				
Age 18	0.035	0.014	0.023	0.021
	(0.051)	(0.051)	(0.050)	(0.050)
Age 19	0.058	0.026	0.040	0.037
	(0.051)	(0.051)	(0.051)	(0.050)
Age 20	0.082	0.037	0.058	0.052
	(0.055)	(0.054)	(0.054)	(0.053)
Family Background				
Ln Family Income	0.009	0.010	0.006	0.005
	(0.009)	(0.009)	(0.009)	(0.009)
Living with family type– Reference group, other family types				
Both biological or adoptive parents	-0.045	-0.033	-0.036	-0.037
	(0.030)	(0.030)	(0.030)	(0.029)
Lone parent	-0.003	0.005	0.003	0.002
	(0.035)	(0.034)	(0.034)	(0.034)
Lives without parents	0.018	0.016	0.006	0.004
	(0.048)	(0.048)	(0.047)	(0.047)
Mother's Education –Reference group Long-Cycle				
Less than high school	-0.107***	-0.096***	-0.093***	-0.080**
	(0.028)	(0.028)	(0.028)	(0.028)
High school	-0.074***	-0.084***	-0.082***	-0.076***
	(0.017)	(0.017)	(0.017)	(0.017)
Short-cycle education	-0.088***	-0.098***	-0.091***	-0.084***
	(0.017)	(0.017)	(0.017)	(0.017)
Medium-cycle education	-0.028	-0.032	-0.033	-0.029
	(0.028)	(0.028)	(0.028)	(0.027)
Mother's education data missing	-0.027	-0.037	-0.038	-0.037
	(0.053)	(0.053)	(0.053)	(0.052)
Father's Education –Reference group Long-Cycle				
Less than high school	0.007	0.012	0.009	0.013
	(0.019)	(0.019)	(0.019)	(0.019)
High school	0.018	0.017	0.013	0.016
	(0.020)	(0.020)	(0.020)	(0.020)
Short-cycle education	0.007	0.003	0.006	0.008
	(0.019)	(0.019)	(0.019)	(0.018)
Medium-cycle education	0.039	0.034	0.029	0.041
	(0.036)	(0.035)	(0.035)	(0.035)
Father's education data missing	-0.092**	-0.088*	-0.093**	-0.091**
	(0.035)	(0.035)	(0.035)	(0.034)
Sample Size	6,770	6,770	6,770	6,770
R-squared	0.032	0.044	0.063	0.081

Table 4: Counterfactual Admissions Constraints: Distribution of Delay (Standard Errors in Parentheses)

	Baseline	Free Entry	Free Entry with no delay	Free Entry Except Med.
Total				
0 years delay	0.5722	0.6306	0.6523	0.6348
	(0.0072)	(0.0072)	(0.0072)	(0.0067)
1 year delay	0.2861	0.2584	0.2319	0.2507
	(0.0049)	(0.0047)	(0.0045)	(0.0047)
2 years delay	0.1418	0.1110	0.1158	0.1144
	(0.0052)	(0.0045)	(0.0046)	(0.0044)

Table 5: Gross flows in the distribution of delay from the baseline to the free-entry experiment

	Free Entry		
	Zero years	One year	Two years
Baseline			
Zero years	0.5576	0.0103	0.0042
One year	0.0493	0.2325	0.0042
Two years	0.0236	0.0156	0.1025

Table 6: Gross flows in the distribution of delay from free-entry to the no-delay experiment

	Free Entry Without Delay		
	Zero years	One year	Two years
Free Entry			
Zero years	0.6306	0.0000	0.0000
One year	0.0156	0.2278	0.0150
Two years	0.0062	0.0041	0.1007

Table 7: Counterfactual Admissions Constraints: Distribution of Field of Study (Standard Errors in Parentheses)

	Baseline	Free Entry	Free Entry Except Med.
Total			
Humantities	0.1008	0.0850	0.0975
	(0.004)	(0.003)	(0.003)
Natural Science	0.1428	0.1159	0.1414
	(0.004)	(0.004)	(0.004)
Social Science	0.3851	0.3631	0.4168
	(0.005)	(0.006)	(0.006)
Engineering	0.2555	0.1933	0.2313
	(0.005)	(0.005)	(0.005)
Medical programs	0.1159	0.2427	0.1130
	(0.004)	(0.008)	(0.004)

Table 8: Gross flows in the joint distribution of delay and field of study from baseline to free-entry

	Free Entry														
	Zero years delay					One year delay					Two years delay				
	Hum.	Sci.	Soc. Sci.	Eng.	Med	Hum.	Sci.	Soc. Sci.	Eng.	Med	Hum.	Sci.	Soc. Sci.	Eng.	Med
Baseline															
Zero years delay															
Hum.	0.0393	0.0003	0.0018	0.0002	0.0050	0.0002	0.0001	0.0005	0.0001	0.0003	0.0001	0.0000	0.0003	0.0001	0.0001
Sci.	0.0004	0.0718	0.0044	0.0010	0.0123	0.0001	0.0003	0.0005	0.0003	0.0005	0.0000	0.0001	0.0002	0.0001	0.0002
Soc. Sci.	0.0009	0.0017	0.1724	0.0014	0.0191	0.0004	0.0004	0.0019	0.0006	0.0008	0.0003	0.0001	0.0010	0.0002	0.0003
Eng.	0.0006	0.0020	0.0080	0.1240	0.0195	0.0001	0.0004	0.0008	0.0007	0.0007	0.0001	0.0001	0.0003	0.0003	0.0002
Med.	0.0001	0.0001	0.0006	0.0002	0.0707	0.0000	0.0001	0.0002	0.0001	0.0002	0.0000	0.0000	0.0001	0.0000	0.0001
One year delay															
Hum.	0.0003	0.0002	0.0014	0.0002	0.0026	0.0245	0.0001	0.0015	0.0000	0.0023	0.0001	0.0000	0.0003	0.0000	0.0001
Sci.	0.0002	0.0005	0.0019	0.0005	0.0044	0.0001	0.0227	0.0012	0.0000	0.0035	0.0000	0.0001	0.0002	0.0001	0.0001
Soc. Sci.	0.0009	0.0010	0.0063	0.0011	0.0096	0.0003	0.0007	0.0885	0.0001	0.0078	0.0002	0.0002	0.0011	0.0002	0.0003
Eng.	0.0005	0.0010	0.0040	0.0014	0.0086	0.0001	0.0007	0.0028	0.0426	0.0067	0.0001	0.0001	0.0003	0.0003	0.0002
Med.	0.0001	0.0001	0.0004	0.0001	0.0020	0.0000	0.0001	0.0003	0.0000	0.0257	0.0000	0.0000	0.0000	0.0000	0.0000
Two years delay															
Hum.	0.0002	0.0001	0.0008	0.0001	0.0012	0.0001	0.0001	0.0008	0.0000	0.0009	0.0136	0.0000	0.0004	0.0000	0.0006
Sci.	0.0001	0.0003	0.0009	0.0002	0.0020	0.0000	0.0001	0.0005	0.0000	0.0014	0.0000	0.0083	0.0002	0.0000	0.0009
Soc. Sci.	0.0005	0.0005	0.0036	0.0005	0.0045	0.0002	0.0003	0.0028	0.0001	0.0034	0.0001	0.0002	0.0463	0.0000	0.0023
Eng.	0.0002	0.0005	0.0018	0.0007	0.0035	0.0001	0.0003	0.0010	0.0001	0.0024	0.0000	0.0002	0.0005	0.0156	0.0016
Med.	0.0000	0.0000	0.0002	0.0000	0.0013	0.0000	0.0000	0.0002	0.0000	0.0010	0.0000	0.0000	0.0000	0.0000	0.0117

Table 9: Gross flows in the joint distribution of delay and field of study from baseline to free-entry-except-medicine

	Free Entry Except Medicine														
	Zero years delay					One year delay					Two years delay				
	Hum.	Sci.	Soc. Sci.	Eng.	Med	Hum.	Sci.	Soc. Sci.	Eng.	Med	Hum.	Sci.	Soc. Sci.	Eng.	Med
Baseline															
Zero years delay															
Hum.	0.0445	0.0004	0.0021	0.0003	0.0000	0.0001	0.0001	0.0003	0.0001	0.0000	0.0001	0.0000	0.0002	0.0000	0.0000
Sci.	0.0005	0.0840	0.0054	0.0012	0.0000	0.0000	0.0002	0.0003	0.0002	0.0001	0.0000	0.0001	0.0002	0.0001	0.0001
Soc. Sci.	0.0010	0.0020	0.1931	0.0017	0.0000	0.0003	0.0002	0.0013	0.0004	0.0002	0.0002	0.0001	0.0007	0.0001	0.0001
Eng.	0.0008	0.0024	0.0096	0.1432	0.0000	0.0001	0.0002	0.0005	0.0004	0.0001	0.0000	0.0001	0.0001	0.0001	0.0001
Med.	0.0001	0.0002	0.0007	0.0002	0.0711	0.0000	0.0000	0.0001	0.0001	0.0001	0.0000	0.0000	0.0000	0.0000	0.0000
One year delay															
Hum.	0.0006	0.0005	0.0026	0.0006	0.0001	0.0271	0.0002	0.0016	0.0000	0.0000	0.0001	0.0000	0.0003	0.0000	0.0000
Sci.	0.0005	0.0013	0.0036	0.0015	0.0001	0.0001	0.0269	0.0015	0.0000	0.0000	0.0000	0.0000	0.0001	0.0001	0.0000
Soc. Sci.	0.0019	0.0027	0.0109	0.0030	0.0002	0.0003	0.0009	0.0971	0.0001	0.0000	0.0002	0.0001	0.0009	0.0001	0.0001
Eng.	0.0010	0.0024	0.0075	0.0039	0.0001	0.0001	0.0008	0.0033	0.0497	0.0000	0.0000	0.0001	0.0002	0.0001	0.0000
Med.	0.0002	0.0004	0.0009	0.0004	0.0000	0.0000	0.0000	0.0003	0.0000	0.0267	0.0000	0.0000	0.0000	0.0000	0.0000
Two years delay															
Hum.	0.0004	0.0003	0.0015	0.0004	0.0000	0.0001	0.0001	0.0009	0.0001	0.0000	0.0147	0.0000	0.0004	0.0000	0.0000
Sci.	0.0003	0.0006	0.0017	0.0007	0.0001	0.0001	0.0002	0.0007	0.0001	0.0000	0.0000	0.0101	0.0003	0.0000	0.0000
Soc. Sci.	0.0010	0.0013	0.0063	0.0015	0.0001	0.0002	0.0005	0.0033	0.0002	0.0000	0.0001	0.0002	0.0505	0.0000	0.0000
Eng.	0.0004	0.0012	0.0035	0.0019	0.0001	0.0001	0.0004	0.0014	0.0002	0.0000	0.0000	0.0002	0.0006	0.0186	0.0000
Med.	0.0000	0.0000	0.0003	0.0000	0.0000	0.0000	0.0000	0.0002	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0137

Supplemental appendices

A Variable construction

Life Time Earnings

To calculate life-time earnings, we begin with the annual earnings for sample members in the first ten post-schooling years, then project these earnings out to age 60.

The projections are based on returns to potential experience estimated in a sample of older cohorts who graduated from the same degree programs between 1971 and 1988. We do not use this sample in the main analysis because their high school grades and high school graduation dates are not included in the registers. However, we know when this sample graduated from their Candidature, their age and sex. We estimate returns to experience separately by sex, program, and institutions, starting with the eleventh year post-candidature by regressing log real earnings on years since candidature and a squared term. We also control for age and cohort. Using those sex-university-program specific slopes, we project real earnings from the eleventh post-schooling year out to age 60. We then calculate the present-value of real earnings discounted at 4%.

Expected Student Financial Aid

Because we can observe in the administrative data the actual amount of education grants (Statens Uddannelsesstøtte) received, we use these values for the financial aid students expect in the pathways that they actually follow. We calculate the present value of aid received using a discount rate of 4% and summing across all the years aid was received. To forecast expected aid in the pathways that were not taken, we assume that students would expect the same total grants independent of which program they study.

Because the means testing for education grants depends on parental income for students who are younger than age 22 before 1987 and younger than age 19 after 1987, expected student financial aid may depend on the number of years of delay. To account for this, we estimate the relationship between education grants and family income for each age. Using these age-specific family-income gradients, we adjust the expected education grants in different periods according to students' ages and family incomes.

B Example of an EMAX

Student who are considering whether to delay entrance into university must evaluate the expected maximum utility in the next period. If a student is qualified with probability one for all programs in the next period, the Emax is:

$$\mathbb{E}\left[\max\left(V^G_{ig+1}, V^S_{i1g+1}, \ldots, V^S_{i30g+1}\right)|P_{ipg}=1 \ \ \forall\, p\right] = \tau \ln\left[\exp\left(\frac{1}{\tau}\bar{V}^G_{ig+1}\right) + \sum_p \exp\left(\frac{1}{\tau}\bar{V}^S_{ipg+1}\right)\right] + \tau\lambda$$

where $P_{ipg} = \mathbb{E}\left[Q_{ipg}|GPA_i\right]$.

However, for most students $P_{ipg} < 1$ for some subset of the programs. When that is the case, the Emax is a weighted average of the expected maximum value from all of the possible combinations of programs for which a student might be qualified next period. The weights are the probabilities associated with being qualified for each combination of programs.

For example, if a student assigns probability of qualification equal to one for 12 programs and probability equal zero for another 16 programs, this leaves 2 programs with uncertain probability of qualification, generating 4 possible choice sets. If the programs are sorted from highest to lowest thresholds then the Emax for this hypothetical student would be:

$$\begin{aligned}
& \mathbb{E}\left[\max\left(V^G_{ig+1}, V^S_{i1g+1}, \ldots, V^S_{ipg+1}, \ldots V^S_{i30g+1}\right) \mid P_{iqg}=0 \quad q \in \{1,12\}, P_{irg}=1 \quad r\in\{15,30\}\right] \\
= \;& P_{i,13,g}P_{i,14,g}\tau \ln\left[\exp\left(\frac{1}{\tau}\bar{V}^G_{ig+1}\right) + \sum_{p=13}^{30}\exp\left(\frac{1}{\tau}\bar{V}^S_{ipg+1}\right)\right] \\
+ \;& \left(1-P_{i,13,g}\right)P_{i,14,g}\tau \ln\left[\exp\left(\frac{1}{\tau}\bar{V}^G_{ig+1}\right) + \sum_{p=14}^{30}\exp\left(\frac{1}{\tau}\bar{V}^S_{ipg+1}\right)\right] \\
+ \;& P_{i,13,g}\left(1-P_{i,14,g}\right)\tau \ln\left[\exp\left(\frac{1}{\tau}\bar{V}^G_{ig+1}\right) + \exp\left(\frac{1}{\tau}\bar{V}^S_{i,13,g+1}\right) + \sum_{p=15}^{30}\exp\left(\frac{1}{\tau}\bar{V}^S_{ipg+1}\right)\right] \\
+ \;& \left(1-P_{i,13,g}\right)\left(1-P_{i,14,g}\right)\tau \ln\left[\exp\left(\frac{1}{\tau}\bar{V}^G_{ig+1}\right) + \sum_{p=15}^{30}\exp\left(\frac{1}{\tau}\bar{V}^S_{ipg+1}\right)\right] + \tau\lambda
\end{aligned}$$

C Minimum GPA Thresholds

Table C.1: GPA Thresholds From the KOT

	Group I (1981-1983)				
	Humanities	Nat. Sci	Soc. Sci	Eng.	Med.
Mean	7.19	7.44	7.7	7.21	9.19
Minimum	6	6	6	6	8.8
Maximum	8.6	8.8	9.4	8.5	9.6
	Group II (1982-1985)				
	Humanities	Nat. Sci	Soc. Sci	Eng.	Med.
Mean	6.5	6.67	6.69	6.09	8.5
Minimum	6	6	6	6	7.1
Maximum	8.0	8.7	8.6	7.1	8.9

Notes: A GPA threshold of 6 implies that supply exceeded demand.

D Estimated Parameters

Table D.2: Model Estimation Results (Standard Errors in Parenthesis)

Value of Schooling			
Father holds Candidature in same field of study	9.367	Program located in own city	4.398
	(1.532)		(0.929)
Mother holds Candidature in same field of study	3.322	Program located in own region	18.464
	(1.660)		(2.668)
Expected years to Candidature completion	-1.870	Student-Teacher Ratio	1.236
	(0.370)		(0.193)
Gender match with faculty	7.530	HS track match with faculty	15.765
	(1.176)		(2.299)
Faculty intercepts, relative to Humanities			
Natural sciences	0.927	Social sciences	-1.008
	(0.865)		(0.826)
Engineering	9.850	Medical programs	11.851
	(1.839)		(2.083)
Value of Delaying			
Local youth unemployment rate	-0.116	Age	-2.309
	(0.043)		(0.409)
Female, first gap year	3.228	Female, second gap year	-1.299
	(0.821)		(0.884)
Math track, first gap year	-11.723	Math track, second gap year	-7.290
	(1.775)		(1.281)
Cohort intercepts, relative to 1981			
1982	-2.411	1983	-1.512
	(0.597)		(0.516)
Preference shocks			
$\exp(\tau)$	2.453		
	(0.143)		

E Model Fit

Table E.3: Model Fit: Distribution of Delay (Standard Errors in Parenthesis)

	In Sample, 1981-83		Out of Sample, 1984	
	Simulated	**Data**	**Simulated**	**Data**
Total				
0 years delay	0.572	0.579	0.544	0.536
	(0.007)	(0.006)	(0.015)	(0.010)
1 year delay	0.286	0.287	0.293	0.295
	(0.005)	(0.005)	(0.011)	(0.009)
2 years delay	0.142	0.134	0.163	0.169
	(0.005)	(0.004)	(0.011)	(0.008)
Males				
0 years delay	0.618	0.631	0.599	0.602
	(0.009)	(0.007)	(0.011)	(0.012)
1 year delay	0.260	0.259	0.255	0.270
	(0.006)	(0.007)	(0.007)	(0.011)
2 years delay	0.122	0.110	0.147	0.128
	(0.006)	(0.005)	(0.009)	(0.009)
Females				
0 years delay	0.488	0.483	0.459	0.426
	(0.010)	(0.010)	(0.014)	(0.016)
1 year delay	0.334	0.339	0.323	0.338
	(0.009)	(0.010)	(0.010)	(0.015)
2 years delay	0.178	0.178	0.217	0.237
	(0.008)	(0.008)	(0.011)	(0.014)
Math Track				
0 years delay	0.630	0.623	0.591	0.568
	(0.008)	(0.007)	(0.012)	(0.011)
1 year delay	0.260	0.266	0.263	0.288
	(0.006)	(0.006)	(0.007)	(0.010)
2 years delay	0.109	0.111	0.146	0.144
	(0.005)	(0.004)	(0.008)	(0.008)
Language				
0 years delay	0.363	0.422	0.353	0.395
	(0.010)	(0.013)	(0.012)	(0.023)
1 year delay	0.378	0.362	0.357	0.326
	(0.007)	(0.012)	(0.008)	(0.022)
2 years delay	0.259	0.216	0.290	0.279
	(0.011)	(0.011)	(0.013)	(0.021)

Table E.4: Model Fit: Distribution of Faculties (Standard Errors in Parenthesis)

	In Sample, 1981-83		Out of Sample, 1984	
	Simulated	**Data**	**Simulated**	**Data**
Total				
Humantities	0.101	0.101	0.098	0.084
	(0.004)	(0.004)	(0.004)	(0.006)
Natural Science	0.143	0.145	0.146	0.153
	(0.004)	(0.004)	(0.004)	(0.007)
Social Science	0.385	0.387	0.407	0.412
	(0.005)	(0.006)	(0.006)	(0.010)
Engineering	0.255	0.255	0.276	0.268
	(0.005)	(0.005)	(0.006)	(0.009)
Medical programs	0.116	0.112	0.074	0.083
	(0.004)	(0.004)	(0.003)	(0.006)
Males				
Humantities	0.052	0.054	0.046	0.045
	(0.003)	(0.003)	(0.003)	(0.005)
Natural Science	0.171	0.148	0.171	0.155
	(0.005)	(0.005)	(0.005)	(0.009)
Social Science	0.386	0.375	0.408	0.402
	(0.006)	(0.007)	(0.007)	(0.012)
Engineering	0.308	0.347	0.322	0.345
	(0.006)	(0.007)	(0.007)	(0.012)
Medical programs	0.083	0.076	0.053	0.052
	(0.004)	(0.004)	(0.003)	(0.006)
Females				
Humantities	0.192	0.189	0.183	0.147
	(0.006)	(0.008)	(0.006)	(0.012)
Natural Science	0.090	0.142	0.105	0.150
	(0.003)	(0.007)	(0.004)	(0.012)
Social Science	0.383	0.408	0.405	0.429
	(0.007)	(0.010)	(0.006)	(0.016)
Engineering	0.158	0.084	0.199	0.140
	(0.004)	(0.006)	(0.005)	(0.011)
Medical programs	0.177	0.177	0.108	0.134
	(0.007)	(0.008)	(0.005)	(0.011)
Math Track				
Humantities	0.062	0.036	0.065	0.039
	(0.003)	(0.003)	(0.003)	(0.004)
Natural Science	0.177	0.179	0.175	0.179
	(0.005)	(0.005)	(0.005)	(0.009)
Social Science	0.310	0.338	0.346	0.370
	(0.006)	(0.007)	(0.006)	(0.011)
Engineering	0.314	0.325	0.329	0.327
	(0.006)	(0.006)	(0.007)	(0.010)
Medical programs	0.137	0.121	0.085	0.086
	(0.005)	(0.004)	(0.003)	(0.006)
Language				
Humantities	0.239	0.334	0.239	0.279
	(0.007)	(0.012)	(0.007)	(0.021)
Natural Science	0.022	0.025	0.021	0.043
	(0.002)	(0.004)	(0.002)	(0.009)
Social Science	0.655	0.560	0.670	0.594
	(0.010)	(0.013)	(0.009)	(0.023)
Engineering	0.044	0.005	0.045	0.013
	(0.004)	(0.002)	(0.004)	(0.005)
Medical programs	0.040	0.076	0.025	0.071
	(0.004)	(0.007)	(0.002)	(0.012)

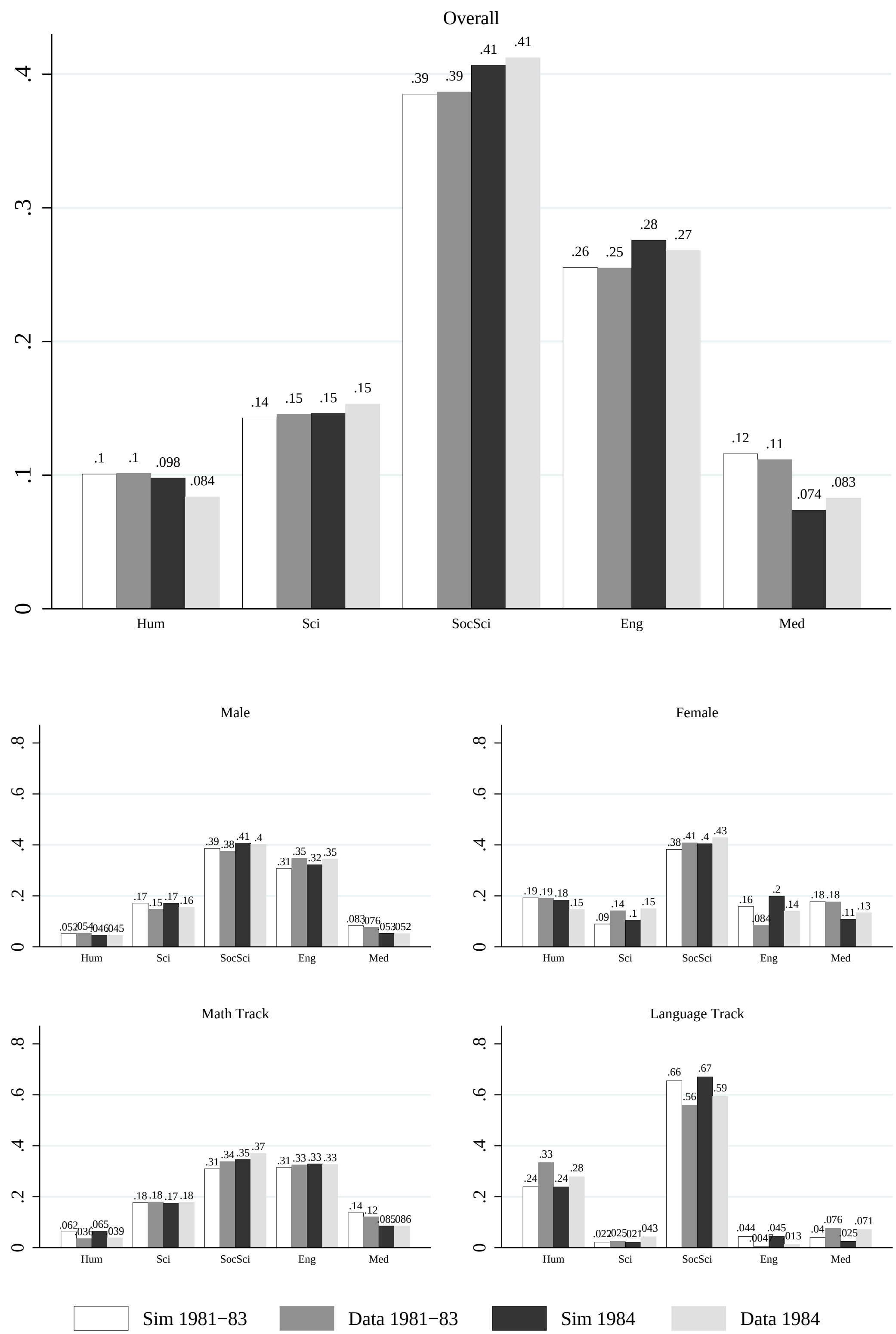


Figure E.1: Faculty Fit: Distribution of Delay

Notes: Model estimated using data from 1981-1983. Data used to assess fit from 1984.