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Field of Study and the Decision to Delay University

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Abstract

Using administrative data from Danish Population Registers, we document a strong relationship between the propensity to delay entering university and the field of study entered. For example, students in the humanities are 2.5 times more likely to have delayed than those in Engineering. We build and estimate a dynamic discrete choice model, in which students choose whether to enter one of 30 university programs or to delay. Delaying has option value because during the sample period, Danish admissions requirements were lower for students with work experience. The model is partially identified by exogenous fluctuations, over time, in program-specific minimum-GPA admissions criteria.

We use the model to estimate the value of delay, conditional on field of study, by comparing the utility students experience after one or two years of delay to the utility they would gain from entering the same program without delay. We then decompose the value of delay into various components including that attributable to earnings during delay and schooling, and lifetime post-schooling earnings. We find that although the costs of delaying, in terms of lost lifetime-earnings, vary according to field of study, that variation can not account for the differences in the propensity to delay. While delayers earn income during their gap years and have on average higher earnings during schooling, this benefit to delaying is relatively uniform across the different fields, and as such does not explain the observed delaying behaviour. We also perform partial-equilibrium counterfactual experiments that manipulate minimum-GPA admissions criteria to investigate whether option value drives differences in the propensity to delay. We find that humanities students do respond most to changes in admissions criteria, but at most the gap in delaying between Humanities and Engineering students closes by a third. Instead, only unobserved differences in the value of delay are large enough to explain the variation in delaying across fields of study. If these unobserved differences are interpreted as preferences, our finding is in keeping with other structural schooling models, and suggests that delay is a potentially important dimension which deserves more attention in that literature.

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1 Introduction

Compared to the amount of attention that is directed toward understanding how wages are affected by the level of education individuals obtain, the issue of *when* education is acquired receives scarcely any attention. A possible reason why the issue of timing garners less attention from economists is that the early canonical models of human capital predict that any period of full-time schooling will occur at the beginning of one's life cycle and investment levels decline monotonically thereafter (e.g. Ben-Porath, 1967; Becker, 1964). In short, because the returns to human capital depend on the span of one's working life, it is best to have the longest horizon over which to reap those benefits. Yet, interruptions in schooling that defy these predictions are observed in many data sets.

In this paper, using Danish administrative data, we focus on individuals who attend university but do not progress directly from high school. Delaying university is a fairly widespread practice in Denmark that increased in prevalence during the 1980's and 1990's.[1] In the 2007 high school graduating cohort, among those who attended university within six years, roughly 1 in 5 went directly from high school.

Delayed entrance occurs throughout Europe, but with less frequency. For example, in recent cohorts of university entrants, 46 percent of students in Norway entered university directly (Orr and Netz, 2011). Delaying university is also observed in North America. In a sample of Canadians who were 20-years old in 2000, among those who had enrolled in post-secondary education, 24 per cent had delayed by 12 months or more (Tomkowicz and Bushnik, 2003). In 2000, almost half of U.S. undergraduates had delayed their post-secondary schooling by at least six months (Horn and Malizio, 2002).

Observations of delaying can be rationalized theoretically by relaxing some of the assumptions

[1] The decision to delay the first entrance into university is often referred to as taking 'gap years', and we adopt this convention.

in the Ben-Porath (1967) model. For example, the early models assume that credit markets are perfect. With credit constraints, periods of work interrupting full-time schooling could be optimal so that students can finance their study. In light of this, Denmark is an interesting case to consider because students are very unlikely to face credit constraints since, during our sample period, there were no direct costs and student grants were widely available.[2]

In this paper, we demonstrate that the propensity to delay university varies significantly across students' fields of study. For example, students in the Humanities are more than twice as likely to delay than students in Engineering. A number of reasons could explain this pattern. Since there is considerable evidence that the returns to education depend on field of study, it might be that the earnings losses associated with delay also vary across this dimension. Alternatively, students might end up in particular fields after delaying because they tried repeatedly to gain admissions to a different field and failed. In Denmark, during our sample period, admissions requirements were effectively lower for students with work experience.

To explore the relative importance of these explanations, we develop and estimate a dynamic discrete choice model. A structural approach is critical in this context because delaying and choosing a field of study are simultaneously determined. Indeed, the decision to delay is essentially the decision not to enter any field of study in any given year. 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 1981-1984 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.

Using the model, we estimate the value of delay conditional on field of study, by calculating the utility a delayer would lose if they had entered the same program without delay. We then

[2]Nielsen et al. (2010) study the effect of an expansion in student aid and find very little impact on enrollments suggesting that constraints did not bind prior to the expansion.

decompose that value into that which can be attributed to observed and unobserved characteristics. We find that although the costs of delaying, in terms of lost lifetime-earnings, vary according to field of study, that variation can not account for the differences in the propensity to delay. Indeed, the impacts of delaying on post-schooling earnings, imply that Engineers should be the most likely to delay. While delayers earn income during their gap years and have on average higher earnings during schooling, this benefit to delaying is relatively uniform across the different fields, and as such does not explain the observed delaying behaviour.

To gauge the extent to which students delay because they are hoping to qualify for a program with a minimum GPA above their own, we perform a number of counterfactual experiments that manipulate GPA cutoffs. In a partial equilibrium counterfactual that eliminates all GPA thresholds, effectively allowing students to enter any program, the estimated fraction of students delaying only falls from 46 percent to 37 percent. Among students who graduated from humanities in the data, and who have the highest propensity to delay, removing admissions constraints reduces delay from 70% to 58%. The effect among Engineering students is smaller, but the differential propensities to delay persists. In the data, the ratio of delay among Humanities to Engineers is 2.5, with no admissions constraints the ratio becomes 1.76.

Taken together these results suggest that neither differences in earnings nor the option value, in terms of admissions, of delaying can fully account for the relationship between delaying and field of study. Instead, unobserved factors constitute most of the value of delay and the differences across field of study drive the variation in the propensity to delay. Interpreting these factors as preferences would be in-line with other structural models in which preferences are found to explain most the variation in schooling choices (Arcidiacono, 2004; Carneiro et al., 2003; Cunha et al., 2005).

The rest of the paper proceeds by first reviewing the relevant literature and then by describing, in brief, the Danish schooling system. In the next two sections, we describe the model and estimation, including the data. The results section that follows first describes the individual characteristics associated with delaying university and documents the correlation between delaying and field of study. Next, we turn to the dynamic discrete choice model, reporting the estimated structural parameters and describing how well the model fits in- and out-of-sample data. We then discuss the estimated value of delay and our counterfactual experiments. Finally, we offer some concluding comments.

2 Previous Research

This paper is among the first to link delaying university to field of study. As such, it is related to both of the literatures which have separately studied these issues. The evidence emerging from the literature which examines the reasons for and consequences of delaying post-secondary education is mixed, likely because of differences in data sets, samples, and the nature of the effect identified.

Credit constraints are frequently cited as a reason for delaying because constrained individuals may postpone university to save money for their education. Kane (1996) uses state level variation to estimate the relationship between tuition levels and delaying university in the NLSY and CPS data sets. He finds that delayed college entry is more pervasive in high tuition states. He interprets his results as evidence that tuition elasticities are overstated by one third because students respond to tuition increases by delaying entry. Also using the NLSY, Carneiro and Heckman (2002) find that 8% of all students are credit constrained in their decision of when to enter university.

In Danish data, credit constraints are far less likely to play an important role in delaying university. During the period we study, no fees were charged at any Danish university and generous grants were available for students from lower income families. For example in 1981, the average student grant in our sample was roughly 5000 USD in 2001 dollars. Until 1988, grant eligibility depended on parents' income for students below the age of 22. However, a reform implemented in that year lowered the age at which parental means-testing was required to 19. Nielsen et al. (2010) study the effect of that expansion in aid and conclude that borrowing constraints were unimportant in Denmark.

Beyond credit constraints, a variety of reasons for postponing university can arise from other constraints or frictions which are frequently ignored in traditional human capital models. For example, interruptions in education may occur because individuals learn about their abilities or labour market opportunities during the intervening periods. It could also be the case that the capacity to acquire human capital depends on age and maturity, making it productive to delay university. If taking time off increases productivity sufficiently, delaying university could have a positive effect on earnings. Thus, outside the framework of Ben-Porath type models, the effect of delaying on earnings is ambiguous, which is reflected in the results from studies estimating these effects.

In U.S. data, Light (1995) finds that individuals who delay by two years receive a wage premium that is 20 percentage points lower than those who complete 16 years of education with no delay. Delays in Light's (1995) data can occur because of interruptions during college or prior to college. Monks (1997) estimates, in a fixed-effects model, the effect of age at college-completion on earnings. He finds that the initial post-college increase in earnings is 4 per cent smaller for individuals who graduate one year older. In his data, Monks (1997) can not distinguish between individuals who graduate later in life because they delayed entry or because they took longer to complete their college education.

In contrast, in a sample of Canadian post-secondary graduates, Ferrer and Menendez (2014) find that wages are higher for those who delayed their entry, particularly for those who worked during the delay. The authors use provincial and national unemployment rates in the years prior to university enrollment to instrument for the decision to delay. As such, the effect they identify is relevant for the population at the margin affected by the instrument. This group is likely to be quite different from our sample. Moreover, their sample includes individuals who may have interrupted their studies for as many as 10 years.

Using Swedish data that is most similar to ours, Holmlund et al. (2008) find that, delaying university by two years is associated with a loss in the discounted present value of lifetime earnings amounting to 40 to 50 percent of one year of age-40 earnings. In their estimates, Holmlund et al. (2008) include fixed effects for interactions between level, length and field of study, essentially estimating the effect of delaying within an education category. They do not, however, allow the impact of delaying to differ across fields of study. Our paper extends this research by allow the value of delay to depend on the chosen field and by also explicitly modelling the joint decisions to delay and enter a particular field of study.

Interest in what determines the decision to pursue a particular field of study and the returns to different fields has been growing recently, perhaps because, as Altonji et al. (2012) point out, wage differences across fields of study can be as large as the average return to university. The first papers in this literature relied on conditional independence assumptions to identify wage differences. Although the effect sizes varied, most of the studies found that the returns to education were highest for those studying engineering and lowest for those in the humanities (for example, see Daymonti and Andrisani, 1984; Altonji, 1993; Finnie and Frenette, 2003).

More recently, in a variety of countries, researchers have taken advantage of certain features of the admissions systems that generate discontinuities around a threshold grade point average.[3]For example, in Chile students apply to enter a specific major and institution simul-

[3]While Kirkeben et al. (2014) provide a more comprehensive list of studies that use similar instruments in different contexts, one such study is worth mentioning here since it uses Danish data. Humlum et al. (2012) use the discontinuity generated by random GPA admissions cut-offs to estimate the impact of delaying university on family formation. They find that students above the GPA cut off of their preferred program are more likely to enter in the year of application, and more likely to have had a child by age 26.

taneously. Admissions are based solely on grades and test scores and are determined by an allocation mechanism, similar to medical residency matching, that generates a threshold which is unknown ex-ante. To identify the effect of field of study, Hastings et al. (2013) compare the earnings of students who 'cross the threshold' of a particular field to those just below the cutoff who enter a variety of different fields. Their estimates are in line with previous research where the returns to crossing the admissions threshold in health, science and technology are largest and smallest for humanities.

Using Norwegian data, Kirkeben et al. (2014) emphasize that estimators based on such exogenous variation in admissions thresholds do not identify the earnings gain of one field relative to another. For example, these instruments do not identify how much one gains in earnings from studying Law rather than Humanities. Instead, what is identified is the return to Law, continuing the example, relative to the weighted average of all the next best alternatives, which need not be Humanities. Kirkeben et al. (2014) go on to argue that identifying the effect on earnings from choosing one field over another requires information on the rankings of preferences for each field of study. Their results suggest that policies to expand particular fields of study will have direct effects on the students who enter the targeted fields but also important indirect effects on the students who enter the fields just vacated.

Our work draws on this literature by using variation in Danish GPA thresholds within the context of a structural model. We do not observe the students' rankings because admissions data is only available beginning in the 1990s. Consequently, as Kirkeben et al. (2014) point out, we cannot identify the earnings-returns to particular fields of study. Instead, we contribute to this literature by examining the value of delay within a field of study, and evaluating possible explanations for the marked differences in the propensity to delay across different fields of study.

3 Danish School System

During our sample period, Denmark had 9 years of compulsory schooling called Folkeskole, corresponding roughly to ages 7 through 16. Those who continued beyond grade 9 could choose between an additional year at Folkeskole (grade 10) or a variety of high schools called gymnasium in Danish: ordinary, business or technical high school.[4] We focus on graduates of ordinary high schools because it was the most common form, and because high school grades were registered only for that type of high school during our sample period.

Additional, we concentrate on students graduating with 5-year Candidature degrees (Kandidatur in Danish). Although 3-year Bachelors degrees are also available in Denmark, we focus on the 5-year degree because they were the most prevalent university level credential. For example, in 1981 among those with a university credential 4.7 percent held a Bachelors degree, 94.2 percent held a Candidature and 1.1 percent held a Doctoral degree. While Bachelors degrees have increased in frequency more recently, they remain the least common university credential. In 2010, 19.3 percent of university graduates held a Bachelors compared to 76.2 percent with a Candidature.

To be eligible for university, gymnasium graduates needed to have achieved a minimum score of 6 on a 13-point grade scheme in high school. Eligible students applied to university through a centralized application system called 'den Koordinerede Tilmelding' or KOT. During the sample period, capacity at each university for specific fields of study was established by the Ministry of Education in consultation with Deans 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'. Students in this group are admitted solely on the basis of their GPA.[5] Another 20 per cent

[4]We use the words, high school and gymnasium interchangeably.

[5]The high school GPA used for admissions was a weighted average of the final exams and the course grade, which, for example, might be given for class participation or quality of homework assignments. Final exams were

were allocated to applicants with work experience. The GPA of applicants applying through this channel, which was called 'Group II', was inflated by a factor that increased with the amount of work experience.[6] Specifically, the GPA of applicants with 9-11 months of experience was inflated by 1.09, and by 1.18 for those with 18 months experience. A third group, roughly 10 to 20 per cent 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.

4 Model

We formulate a three-period dynamic model where individuals choose between delaying or entering one of 30 different university programs. The initial period, labeled period zero, corresponds to the year a student completes their terminal high school diploma. In each period, students

standardized across all high schools and were evaluated by the students' teachers as well as external examiners assigned by the Ministry of Education.

[6] This admissions class differs from the current system, first introduced in 1991, called 'Quota 2'

decide whether to enter a program for which they are qualified, or to delay entrance. Entering a program is an absorbing state and by the third period everybody has entered a program. In other words, we condition on delaying at most two years.[7]

Qualifying means the student's own high school GPA is above a program- and year-specific threshold GPA in the relevant admissions class. Students entering directly from high school apply through Group I, and after delaying students apply through Group II. Students applying through the Group II admissions category have their GPAs inflated according to their work experience. Unfortunately, the work experience that qualified for this GPA-adjustment is not recorded in the data and any available measures are poor proxies.[8] As such, we assume that everybody has the maximum GPA adjustment. Specifically, in our model students who delay by one year have their GPA adjusted as if they worked for 12 months, and those who delayed by two years receive the maximum adjustment as if they had worked for 18 months. This will tend to inflate the value of delaying, particularly for programs with high GPA thresholds. As we will demonstrate, the model, if anything, under-predicts delaying.

In a given period, we assume that students can observe the threshold GPAs and thus know before committing for which programs they are eligible. In practice, students would not have known the thresholds when they first applied in June. However, before 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.

For most programs, threshold GPAs vary from year to year depending on relative demand, when a student makes the decision to delay, she does not know which programs she will be eligible for in the subsequent periods. There is, however one program–Humanities at Aalborg

[7]We discuss this restriction in the Data section which follows.

[8]We tried to calculate the GPA multipliers using several different measures of labour force participation. For each measure, there were many individuals who, according to our measure, were not eligible for the program they eventually entered. In particular, for students in Medicine and Law our measures under predicted eligibility by roughly a third.

University–that never has a GPA cut-off in our sample period. We treat that program as the numeraire program and normalize its associated utility to zero. This program acts as an outside option in all periods.

4.1 Utility of schooling and delaying

It is useful to think of the indirect utility of a particular field of study as occurring in two separate periods, during and post-schooling. In the post-schooling period, the indirect utility of a program depends on the expected present discounted value of lifetime earnings plus a random shock.

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

Each program, indexed by p, is associated with a different stream of earnings, which also depends on whether university was delayed. The years of previous delay are indexed by g, such that $g = 0$ means an individual transitioned directly from high school to university. The expected present value of earnings, for each program and year of delay combination, is defined as relative to the numeraire program and varies across individuals according to their ability, measured by high school grades, their gender, age at high school graduation and their region. We describe the construction of $PV\ earn_{ipg}$, as wells as the other variables, in more detail in Appendix A.

Indirect utility, while in school, varies according to years of delay, characteristics of the program, as well as characteristics that are common across the broader 'faculty' or field of study (indexed by f):

$$\upsilon^S_{ijpg} = \alpha_{fg} + \alpha_{jf} + \alpha_x X_{ip} + \alpha_d \mathbb{E}\left[dur\right]_{pg} + \mathbb{E}\left[earn\right]_{pg} + \mathbb{E}\left[SFA\right]_g + \epsilon^S_{ipg} \tag{2}$$

In equation (2), the delaying index, g, also indicates the period. Thus, for example, υ^S_{ijp0} is the indirect utility of entering program p in period 0 after 0 years of delay.

Within the vector X_{ip}, there are a set of program characteristics, which also vary by individual. Indicators for whether one's mother and father hold a candidature in the program's field of study are included to capture any role model effects or intergenerational correlation in talents. Indicators for whether the program is in the same city or region in which the student lived during their last year of high school measure some of direct costs of schooling.

Utility while in school also depends on how much individuals earn while in school, how much student financial aid they receive, and how long it will take to complete their studies. None of these factors are known with certainty at the time students make their decisions to enter a program or delay. We assume that individuals expect to earn the average among those who enter the same program with the same years of delays $\mathbb{E}\left[earn\right]_{pg}$. Similarly, the expected duration of studying, $\mathbb{E}\left[dur\right]_{pg}$ is the average within each program and years of delay combination. The expected amount of student financial aid, $\mathbb{E}\left[SFA\right]_{g}$, varies across periods because whether or not family income is taken into account when determining eligibility depends on the students' age. The idiosyncratic randomness associated with schooling preferences are reflected in ϵ^{S}_{ipg}.

The indirect utility of schooling also includes a separate intercept, α_{fg}, for each faculty and years-of-delay combination. This allows average utility, holding program characteristics constant, to vary across fields of study and years of delay. Finally, α_{jf} represents unobserved heterogeneity in preferences for each field of study, which is modeled as m discrete mass points, frequently referred to as 'types'.

Students compare the value of entering any of the programs against the value of delaying entrance. The indirect utility from delaying university by one year, conditional on having delayed by g years is:

$$v^{G}_{ijg} = \gamma_j + \gamma_a age_{ig} + \mathbb{E}\left[earn\right]_{g} + \epsilon^{G}_{ig} \tag{3}$$

The utility of delaying depends on the students' unobserved type, γ_j, their current age, how much they expect to earn during the year of delay, and a random component ϵ^G_{ig}.

4.2 Solution

The problem of jointly choosing when and which program to enter is solved, beginning in the last period and working backward, by comparing the functions which, respectively, characterize the value of delaying university versus entering program p in period g:

$$\begin{aligned} V^G_{ijg} &= \upsilon^G_{ijg} + \beta\mathbb{E}\left[\max\left(V^G_{ijg+1}, V^S_{ij1g+1}, \ldots, V^S_{ijpg+1}, \ldots V^S_{ij30g+1}\right)\right] \\ V^S_{ijpg} &= Q_{ipg}\left(\upsilon^S_{ijpg} + \rho\mathbb{E}\left[\upsilon^E_{ipg}\right]\right) \quad p \in \{1, \cdots, 30\} \end{aligned} \tag{4}$$

The annual discount rate is β, while ρ deflates $\mathbb{E}\left[\upsilon^E_{ipg}\right]$ by the expected duration of the program.[9]

In each period g, prior to committing, the student observes ϵ^G_{ig} and the set of ϵ^S_{ipg}. She also knows whether she is qualified for a program in that period. If a student is qualified $Q_{ipg} = 1$ and zero otherwise. This specification means that a program has no current value if the student is ineligible. The student does not know the value of future preference shocks nor does she know which programs she will be qualified for in subsequent years.

Solving for $\mathbb{E}\left[\max\left(V^G_{ijg+1}, V^S_{i1jg+1}, \ldots, V^S_{ijpg+1}, \ldots V^S_{ij30g+1}\right)\right]$ means taking expectations over the unknown future preference shocks, ϵ^G_{ig+1} and all of the ϵ^S_{ipg+1}, and also forecasting the probability of qualifying for a program under the Group II admission class. We assume that students' believe the Group II GPA thresholds follow a random walk:

$$THGPA^{II}_{pg} = THGPA^{II}_{pg-1} + \eta_{pg} \tag{5}$$

[9]The annual discount rate is 4%. We do not estimate these parameters and in practice the results change very little under different discount rates.

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 use the faculty-specific standard deviations 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

This specification allows us to greatly reduce the dimensionality of the problem.[10] If a student's GPA is more than σ_{η_f} above the threshold this period, she believes she will also be eligible next period. Conversely, if a student's GPA is more σ_{η_f} below the GPA threshold this year, she believes she will be ineligible next year. The number of programs for which a student is uncertain she will qualify next period will depend on the student's GPA and the magnitude of σ_{η_f}.

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, the probability of being qualified in the next period is:

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

This specification treats changes in the threshold as unanticipated and conditionally independent of individual behaviour. Uncertainty regarding future GPA thresholds will generate incentives that vary across individuals. For example, those that are very close to, yet above, the threshold of their preferred program are less likely to delay because there is a chance that next period they will not be eligible for their preferred program. For individuals who are close to but below a threshold, delaying offers a second chance at being eligible for their preferred program.

[10] If for each program the probability of being eligible in the next period was neither zero nor one, the student would face 2^{30} different possible choice sets.

For yet another set of students, who have very high grades, the randomness of GPA thresholds generates no incentives.

Finally, we can fully characterize the solution with a closed form by making the further parametric assumption that the preference shocks are distributed as Extreme Value (Type 1), with a location of zero and scale of τ. The problem is solved, beginning in the last period and working backward, by comparing the functions which characterize the value of entering each program and delaying university.

Solution in Period 2

Since we restrict our sample to those who enter one of the 30 degree programs within 3 years, at most, our sample members take two gap years. As such, conditional on having delayed by two years, students choose the program p for which $V^S_{ijp2} \geq V^S_{ijq2}$ for all $q \neq p$.

In period 2, students know both Q_{ip2} and ϵ^S_{ip2}, but not ϵ^E_{ipg}. Since ϵ^E_{ipg} has an Extreme Value distribution, $\mathbb{E}\left[PV\ earn_{ipg2} + \epsilon^E_{ipg}\right] = PV\ earn_{ipg2} + \tau\lambda$, where $\lambda = 0.577$ is Euler's constant. The period 2 value functions can, therefore, be written as:

$$V^S_{ijp2} = Q_{ip2}\left(\upsilon^S_{ijp2} + \rho\left(PV\ earn_{ip2} + \tau\lambda\right)\right) \tag{6}$$

Solution in Periods 0 and 1

In periods 0 and 1, students choose whether to enter one of the programs or to delay by one year. Thus, the decision rule is, if V^G_{ijg} is greater than all the V^S_{ijpg}, the student delays. If not, then the student enters the program for which V^S_{ijpg} is largest. Since entering a program is a terminal choice, in each period the schooling-value functions have the same structure as (6).

The value of delaying in this period depends on the student's expected choice in the next period:

$$V^G_{ijg} = \gamma_j + \gamma_a age_{ig} + \mathbb{E}\left[earn\right]_g + \epsilon^G_{gi} + \beta\mathbb{E}\left[\max\left(V^G_{ijg+1}, V^S_{ij1g+1}, \ldots, V^S_{ijpg+1}, \ldots V^S_{ij30g+1}\right)\right] \tag{7}$$

McFadden (1977) has shown that when preferences have an extreme value distribution the Emax will have a closed form. If a student was qualified for all programs in the next period with probability one, then the closed form for the Emax in (7) would be:

$$\mathbb{E}\left[\max\left(V_{ijg+1}^{G}, V_{ij1g+1}^{S}, \ldots, V_{ij30g+1}^{S}\right) | P_{ipg} = 1 \ \ \forall\, p\right] = \tau \ln \left[\exp\left(\frac{1}{\tau}\bar{V}_{ijg+1}^{G}\right) + \sum_{p} \exp\left(\frac{1}{\tau}\bar{V}_{ijpg+1}^{S}\right)\right] + \tau\lambda$$

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

However, because the GPA thresholds are random, in general, students do not know for certain for which programs they will be eligible in future periods. Thus, solving for the value of delaying involves integrating over the possible choice sets. For example, suppose there are 12 programs for which a student is certain she will be eligible next period, and 16 programs for which she is certain she is not eligible. This leaves 2 programs over which she is uncertain, which in turn generates 4 possible choice sets. If the programs are sorted from highest to lowest thresholds then the Emax for this hypothetical student would be:

$$\begin{aligned}
& \mathbb{E}\left[\max\left(V_{ijg+1}^{G}, V_{ij1g+1}^{S}, \ldots, V_{ijpg+1}^{S}, \ldots V_{ij30g+1}^{S}\right) \ | \ P_{ipg} = 0 \quad p \in \{1,12\} \ P_{ipg} = 1 \quad p \in \{15,30\}\right] \\
= \ & P_{i,13,g} P_{i,14,g} \tau \ln \left[\exp\left(\frac{1}{\tau}\bar{V}_{ijg+1}^{G}\right) + \sum_{p=13}^{30} \exp\left(\frac{1}{\tau}\bar{V}_{ijpg+1}^{S}\right)\right] \\
+ \ & \left(1 - P_{i,13,g}\right) P_{i,14,g} \tau \ln \left[\exp\left(\frac{1}{\tau}\bar{V}_{ijg+1}^{G}\right) + \sum_{p=14}^{30} \exp\left(\frac{1}{\tau}\bar{V}_{ijpg+1}^{S}\right)\right] \\
+ \ & P_{i,13,g} \left(1 - P_{i,14,g}\right) \tau \ln \left[\exp\left(\frac{1}{\tau}\bar{V}_{ijg+1}^{G}\right) + \exp\left(\frac{1}{\tau}\bar{V}_{ij,13,g+1}^{S}\right) + \sum_{p=15}^{30} \exp\left(\frac{1}{\tau}\bar{V}_{ijpg+1}^{S}\right)\right] \\
+ \ & \left(1 - P_{i,13,g}\right)\left(1 - P_{i,14,g}\right) \tau \ln \left[\exp\left(\frac{1}{\tau}\bar{V}_{ijg+1}^{G}\right) + \sum_{p=15}^{30} \exp\left(\frac{1}{\tau}\bar{V}_{ijpg+1}^{S}\right)\right] + \tau\lambda
\end{aligned}$$

4.3 Estimation and Identification

Since the solution has a closed form, we use Maximum Likelihood to estimate the parameters of the model. If for each period g, conditional on type $j = J$, $[S_{ipg} \mid j = J] = 1$ when a student enters program p and $[G_{ig} \mid j = J] = 1$ when the student delays entrance, then an individual contribution to the likelihood function is:

$$\begin{aligned} L_i = \sum_{j \in \{1,2\}} \mathbb{P}[j = J] \quad * \quad & \left\{ \prod_{p=1}^{30} \mathbb{P}[S_{ip2} = 1 \mid j = J]^{S_{ip2}} \right. \\ * \quad & \prod_{p=1}^{30} \mathbb{P}[S_{ip1} = 1 \mid j = J]^{S_{ip1}} \, \mathbb{P}[G_{i1} = 1 \mid j = J]^{G_{i1}} \\ * \quad & \left. \prod_{p=1}^{30} \mathbb{P}[S_{ip0} = 1 \mid j = J]^{S_{ip0}} \, \mathbb{P}[G_{i0} = 1 \mid j = J]^{G_{i0}} \right\} \end{aligned} \tag{8}$$

The likelihood conditional on type is then integrated over the probabilities of each type ($\mathbb{P}[j = J]$). Under the assumption that the errors have an Extreme Value distribution, the choice probabilities take the familiar logit form. Unlike a static model, a dynamic logit does not require 'independence of irrelevant alternatives' because the value of particular decisions are a function of the other choices through the continuation value (Rust, 1994).

In total, there are 28 parameters to estimate. When there are two distinct types of heterogenous preferences, there are 6 type-specific intercepts plus the parameter that determines the distribution of types. In the schooling utility functions there are 14 faculty- and delay-specific intercepts to identify, because we normalize the intercept for entering Humanities without delay to zero. Additionally, there are 5 slope coefficients in the value of schooling and 1 in the value of delay. The last parameter is the scale of the distribution of the idiosyncratic preference shocks.

The observed program choices identify, up to scale, the slope parameters in the utility of schooling equations. For example, consider the coefficient on the indicator that a program is located in one's home town. If two programs were identical except that one program was located in one's home town and the other was not, then the relative enrollment rates in those programs would identify the coefficient. Holding program and period characteristics constant, the intercepts are identified by differences in the distribution of program-specific enrollment rates across periods. Since a program only has value if one can enter the program, the exogenous variation in GPA thresholds helps identify these parameters.

In two ways, the GPA thresholds are also important in identifying the value of delay. First, the continuation value of delaying is a function of expected GPA thresholds. Because we have four different high school graduation cohorts in our data, the expected GPA thresholds for each program, both one and two periods ahead, will vary. As such, differences in the propensity to delay across cohorts help identify the value of delay. Second, within a period, the thresholds identify the set of programs for which an individual is qualified. Importantly, conditional on GPA and years of delay, the set of programs for which a student is eligible will exogenously vary across cohorts. When individuals delay, their choice reveals that the value of delay must be larger than the value of all the programs for which the individual is qualified.

Finally, the estimation method will choose τ, the scale parameter, to fit differences in enrollment rates that are unexplained by the average choice-specific utilities, including differences in lifetime earnings. If there is, for example, a small difference in the average value of entering Law compared to the value of entering Humanities, but very large differences in the enrollment rates, the model will estimate a large value for τ. In other words, if there is large variation in choices in response to small variations in average utilities, then the variation in random shocks must be large.

5 Data

We use data from the Danish population registers, which is administrative data covering 100% of the population in the years 1981 to 2009. Using the registers, we identify a sample of graduates with Candidatures who entered university within 2 years of their terminal gymnasium program.[11] We focus on students who graduated from gymnasium from 1981 to 1984 and who entered one of 30 different programs at the 8 major universities in Denmark.[12] Table 3 lists each of the sample programs categorized by university and field of study. There are five broad fields of study, Humanities, Natural Sciences, Social Sciences, Engineering and Medicine.[13] The programs which fall under each field of study are determined by the Statistics Denmark education classification. We exclude from the sample students who entered programs that were not consistently coded or were designated as Arts programs, such as music, because admission to these programs may involve auditions or the assessment of portfolios. Overall, the programs in our sample represent 85 per cent of the students admitted to a Candidature at the 8 universities during the sample period.

We restrict our sample to individuals who were born in Denmark and graduated from a Danish ordinary high school[14] (almindelig gymnasium), between the ages of 18 and 20, in the years 1981 through 1984. Our sample ends with the 1984 cohort because the 1987 report containing the relevant admissions information does not contain the GPA thresholds.[15] To ensure that we can

[11]Some students obtain more than one credential at the gymnasium level. We consider the last program as their year of graduation from gymnasium.

[12]In our sample period, the Aarhus Business School was a separate institution. More recently it was subsumed under Aarhus University.

[13]We define the student's field of study according to the program they entered first. Students who might want to switch programs would be required to apply again through the normal admissions process. In practice, very few students switch programs. In the second year, 96 percent of students in the sample are still in the same program defined by an 8 digit Statistics Denmark classification. After three years, 90 percent persist in that same program. Within the five broader categories of field of study, 94 percent graduate with a Candidature in the same field of study they first entered.

[14]We only consider graduates from ordinary high schools because, prior to 1996, GPA was registered for only this type of high school. Over the sample period, 87 per cent of Danish high school graduates, who ever attended university, had graduated from ordinary high schools.

[15]The omission is not driven by policy, the thresholds are just not recorded in the archived report. Thus, our

observe the sample in the labour force for at least a decade, we further restrict the sample to individuals who took less than 10 years to complete the Candidature. That means that our sample members graduated from university in the years 1986 through 1996. Being able to observe the sample in the labour force over a relatively long horizon is important because theory suggests that a key cost of delaying is lost earnings due to less post-schooling experience over the whole lifetime.

We focus on graduates primarily to simplify the model which already has 90 decision nodes. The relationship between delaying and field of study that we document among graduates is very similar to that observed among all university participants. We further restrict the data to students who entered university within two years of high school. Although delay is very common in Denmark, most university participants enter within two years of high school. Specifically, among all Gymnasium graduates in the years 1981 to 1984 that entered university before age 30, 79% had entered within 2 years. Another reason we censor after two years of delay is because the GPA multiplier under the Group II admissions class is maximized at 18 months, thus we do not lose any important changes in the dynamic incentives to delay. Finally, there are two practical reasons for this sample selection. First, because the GPA thresholds are missing from the 1987 report, expanding the data by an additional year of delay would mean losing an entire cohort of data. Second, while each year of delay adds 30 branches to the possible pathways in the model, relatively few observations are added with which to identify the model.

The data is created by merging several registers containing information reported to Danish authorities for a variety of purposes, some of which are administrative (eg. taxes, pension schemes, student grants) and some of which are for statistical reporting (student enrollment, graduation dates, occupational classification). In this paper, we use data from four different registers. The first is the Danish Student Register, which contains annual records for all individuals

sample period ends in 1984, because students who graduated in 1985 and who delayed by two years would have been admitted according to the 1987 thresholds.

who attended any level of schooling in Denmark. Every educational institution that is regulated by the government reports by law to Statistics Denmark, through the Ministry of Education. Both enrollments and credentials obtained are recorded, including specific dates of initial enrollment and completion. The specific institution and program is also recorded. For university programs, we have very detailed information about the type of degree program students enrolled in and whether they obtained the credential. For individuals attending ordinary high schools, we observe their average high school grades, which are used to qualify for university.

The second registry included in our data set is the Integrated Database for Labour Market Research (IDA), which contains annual information about socioeconomic variables (e.g., age, gender, children, marital status, geographical location etc.) and labour market information (e.g., labour market status, level of employment, occupations, etc.). Data from this registry is used to construct our lifetime earnings measures, as well as earnings during schooling and years of delay. We use the third registry, a family register, to link the individuals to their parents and construct detailed information about family background. Finally, the fourth register is an income register from which we obtain annual records of the amount of student financial aid received. We summarize the sample data by field of study in Table 1 and by years of delay in Table 2.

The GPA thresholds for admissions to each of the programs under Group I and II were collected from archival reports from KOT called 'Hovedtal'. 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 scanned and cleaned the hard copy reports for 1981 to 1986, generating digital files.

We summarize the GPA threshold data by field of study in Table 4. In Figure 5, we show the changes in the GPA thresholds for each program individually during the sample period. For

Group I, shown in the top panel, the deviations in GPA thresholds can be quite large, sometimes swinging by 2 points from one year to the next. To put that into context the standard deviation of grades in the sample is .82, and 1.2 points separates the top and bottom quartiles. There is far less variation in the Group II GPA thresholds, shown in the bottom panel of Figure 5. This is primarily because there are a number of programs for which supply of Group II seats exceeds demand, implying no GPA cutoff.

6 Results

6.1 Who delays?

Before presenting the structural model, we begin by describing some patterns in the data using reduced form regressions that compare the characteristics of individuals who delay university by one or two years to those who transition directly from high school. Table 5 reports results from four different regressions, including in Columns 1 to 3 the marginal effects from Probit regressions and in Column 4 an OLS regression, where we treat years of delay as if it were linear. The key conclusions that can be drawn from Table 5 are generally consistent across the different specifications.

Women are more likely to delay than men, although conditional on delaying they are no more likely to take more than one year. This is despite the fact that that some fraction of the men delaying university may have been participating in compulsory military service.[16] Individuals with higher grades are less likely to delay. This correlation is unsurprising if one expects delay

[16]During the sample period, military service was compulsory for a fraction of 18 year-old men selected by lottery. In 1979, 27 per cent of all 18 year-old men were conscripted while in 1989, 24 percent were conscripted (Sorensen, 2000). We are unfortunately unable to explore this further because military service is not well observed in the Danish registers. There is, however, no reason to expect that compulsory military service would be correlated with field of study.

to be more common among students who are trying to enter programs through the Group II admissions class. Study line, the curricular concentration in high school, is also a very strong predictor of delay. Students who pursue the language line (as opposed to the math line) are almost 16 percentage points more likely to delay university.

Parental education and in particular mother's education also predicts delaying university. If parental education was correlated with credit constraints, one would expect that children from less educated families would be more likely to delay university. The reverse appears to be true in our sample of Danish students. Children whose mother's completed a long-cycle degree, the same level of education from which our sample members have graduated, are most likely to delay university. It is also worth noting that the fraction of young people in the student's home town who were unemployed in their high school graduation year does not predict delaying.[17]

Access to administrative data linking family background characteristics to education histories permits a fairly rich set of covariates for these regressions. Yet, overall, these measures of individual and family characteristics explain very little of the variation in delaying. The r-squared and pseudo r-squares are all less than 10 per cent.

6.2 Field of study and delay

Although students' observable 'pre-university' characteristics explain very little of delaying, there is a very strong relationship between students' decisions to delay university and enter different fields of study. The fraction of graduates who delayed from each of the five fields of study are reported in the first rows of Table 1. Across the whole sample, 56 percent enter university directly from high school. The propensities to enter directly among graduates in the Social and Natural Sciences are at or near the average at 56 and 52 per cent respectively. Humanities graduates

[17] Sievertsen (2016) finds that local unemployment rates predict the timing of enrollment in any form of post-secondary schooling. While he does not present any evidence that enrollment in university, in particular, is related to fluctuations in unemployment, his results suggest that completion of university is not affected.

are by far the most likely to delay entrance. Indeed, only 3 in 10 Humanities students entered without delay. This behaviour is in stark contrast to Engineering graduates, among whom 73 percent enter university directly. Medical students delay more often than average but less often than Humanities students. While the correlated propensities to delay and enter particular fields are similar whether considering one or two years of delay, the differences are more pronounced with two years of delay.

Understanding what drives these patterns is non-trivial because field of study is also highly correlated with earnings. This is particularly true in Denmark because occupation is closely linked to one's field of study and earnings are often negotiated by unions within sectors. The top panel of Figure 1 illustrates the relationship between delaying, earnings and field of study. Each observation in the scatter plot represents a specific program in a given year. The horizontal axis measures the proportion of those students who delayed entrance and the vertical axis measures the average discounted lifetime earnings in real 10 millions of Danish kroner. The colours of the observations represent different fields of study while the shapes are different universities.

Although there is variation across universities in both earnings and delaying, these differences are not as pronounced as the differences across field of study. The pattern of clustering by field of study demonstrates a high degree of sorting. Mean earnings are high and delay low for Engineering observations while earnings are low and delay high for Humanities students. While there is more overlap with the remaining three faculties, overall the data reveals a negative correlation between mean earnings and delaying.[18]

One interpretation of the top panel of Figure 1 is that the patterns are driven by differences in preferences or productivity. If the only net cost of delaying was lost earnings due to less post-schooling experience, then it would be relatively cheaper for those who delay to enter fields of

[18]The relatively low earnings among Medical graduates stems from the fact that these individuals are most likely to have self-employment income. We estimated our model using lifetime income instead of earnings and none of the results or conclusions change meaningfully.

study where earnings, and hence losses, are lower. Additionally, the factors that lead individuals to value non-market above market activities might jointly influence the decisions to enter low-paying occupations and defer university. Of course, part of the reason some occupations pay less, on average, than others is that less productive individuals sort into those jobs.

A different reading of the figure is that the patterns represent constraints rather than choices. The highest paying occupations might be those that are the most difficult to enter. Perhaps, the best and brightest are able to enter those fields of study directly from university. Less competitive students might delay to gain a second opportunity to enter a preferred program. The sorting observed here could result if the least successful of these 'strategic' delayers cluster in the lower paying fields of study.

The bottom panel of Figure 1 suggests that the latter story is unlikely to account entirely for the relationship between field of study and delay. This figure is the same as the upper panel except that the vertical axis measures the minimum GPA required to enter a program under the Group I admissions class. A number of programs are located at a GPA threshold of 6 because there was excess supply in these program-years, thus everybody who applied could enter. Very little pattern is evident in this figure. A notable exception is that the medical programs are clustered with very high GPA thresholds and with a propensity to delay between .4 and .6. As we will discuss later, the high GPA thresholds in medicine do account for some delay.

6.3 Estimates of model parameters

Next, we turn to the estimates of our dynamic discrete choice model. In Table 6, we report the parameter estimates and standard errors for the model with and without the unobserved-heterogeneity types. We estimated the standard errors using the inverse of the outer product of the numerical gradient vector evaluated at the vector of estimated parameters. The log-likelihoods are also reported for each specification, and based on a likelihood ratio test, the model without type heterogeneity can be rejected with a high level of significance.

The coefficients that capture how program characteristics affect utility, reported in the second panel, are all statistically significant. In contrast, the parameter that allows utility during the year of delay to depend on age is only marginally statistically significant in the model with type heterogeneity and not all in the model without types. Interestingly, the size of the coefficients on program characteristics are similar in both specification. In most cases, the difference is less than either standard error.

As one would expect, the intercepts in the value of schooling, reported in the top panel, do differ substantially across the specifications. These intercepts can be interpreted as shifts in average utility relative to the value of entering a Humanities program without delay.

The introduction of unobserved heterogeneity allows the correlation in the utility between field of study and delaying to vary across the types. Since for 'Type 1', the type-specific intercepts are normalized to zero, the estimates reported in the bottom panel of Table 6 correspond to 'Type 2'. Since the estimated type-intercept in the value of delay is negative, this suggests that the second type has lower average direct utility from delaying. In the value of Engineering, the Type-2 intercept is not statistically different from zero, but in the value functions for each of the other fields these intercepts are significantly negative. Taken together, these imply that compared to the first, the second type is more likely to enter Engineering without delay.

Finally, the parameter τ, reported in the third panel, establishes the scale of the preference shocks. The estimated value of 1.31 and 1.15 implies the distributions of shocks, with and without type-heterogeneity, respectively have means of .76 and .66 and standard deviations of 1.68 and 1.47. Since utility is denominated in 10 million real DKK (year 2000), these shocks should be interpreted as quite large relative to the average present value of post-schooling earnings, which is 1.35.

6.4 Model fit

Because we are primarily interested in why the propensity to delay varies across fields of study, to evaluate how well the model fits the data, we focus on the distribution of delay conditional on field of study. We also show how students are distributed across fields of study. In Figure 2, we compare the distributions observed in the sample data to distributions simulated using our parameter estimates. We generate the simulated distributions by randomly drawing preference shocks 100 times and then determining the distribution of choices conditional on those shocks.

The top panel of Figure 2 demonstrates that our simulated results match the delay decisions exceptionally well for Humanities, Natural Sciences, Social Sciences and Engineering. For students who study in Health and Medicine, we under-predict delaying by 3.8 percentage points overall, equally over-predicting delay by one and two years.

The model's capacity to match field of study is plotted in the bottom panel of Figure 2. Once again the simulated results are very close to the data. This should be expected, in part because we are matching the data used to fit the model, but also because program participation is constrained by the exogenously determined GPA thresholds.[19]

6.5 Delaying under Counterfactual GPA Thresholds

Using the parameters estimated in the model, we perform two counterfactual experiments that alter the GPA thresholds faced by students. We impose the threshold change, simulate a set of shocks 100 times, and then summarize the resulting choices of field of study and years of delay. The goal of these experiments is to help demonstrate the extent to which delaying is a strategic response to admissions constraints.

In each of the experiments, we allow the number of position available in all programs to

[19]Figures illustrating how well the model fits data not used in estimation are available in a supplemental appendix

expand to meet demand. We also hold expected life-time earnings constant for each choice pathway. Additionally, since, in our model, we condition on completing a Candidature, our counterfactual experiments do not allow for new participants and graduates. With this in mind, each experiment expands the set of choices available. This is important because if we restricted the choice set, some students might prefer 'no university' to the constrained set of choices. Essentially, we do not allow for any general equilibrium effects stemming from, for example, changes in the relative number of doctors. As such, it is important to keep in mind that these experiments are not informative about broad policy effects, but are instead intended to reveal how the existing stock of graduates of Candidatures would respond to changes in the admissions constraints.

In Figures 3 and 4, we show the distributions of delay and field of study that are generated by the two experiments. In the top panel of Figure 3, we plot the delay distributions conditional on the field of study chosen in the counterfactual experiment, while the bottom panel conditions on the baseline field of study. In the first experiment labelled 'Free entry', we remove the GPA thresholds from all programs in all periods. This means that students face no admissions constraints and no uncertainty about qualifying for programs in future periods.

Using the simulated results from the main model as a baseline, the fraction of students entering without delay is 9 percentage points higher when students are eligible for all programs. This change, which represents 19.5% of all delay in the baseline model, is primarily driven by a net reduction in the fraction of students delaying by two years. This result is unsurprising since the Group II GPA multiplier is largest after two years. However, because some individuals are *more* likely to delay in the 'free entry' experiment, the net reduction understates the extent to which admissions criteria affect the decision to delay.

Delaying by one year increases by 4 percentage points among those who enter Medical fields when there are no admissions constraints. There are at least two reasons for this increase. First, students who value delaying but who were previously not eligible switch into medical programs when the admissions criteria are removed. As Figure 4 illustrates, the fraction of students who enter Medical programs more than doubles. Although the shares entering all of the other programs fall, the decline is proportionally largest in the Humanities, who in the baseline case are the most likely to delay. Second, some students entering Medicine in the baseline case may have wanted to take a gap year, but were just above the GPA-threshold and did not want to risk the possibility of being ineligible in the next year. The bottom panel of Figure 3 shows that, among students entering Medicine in the baseline case, delaying by one year did increase, but only by 2 percentage points.

The second experiment we perform replicates the Free Entry experiment, except that the GPA thresholds for medical programs remains in place, including the uncertainty over future thresholds. In this experiment the dramatic increase in Medical students that occurred in the previous counterfactual is essentially impossible. It also eliminates the incentive to delay among Medical students who are just above the threshold. Consequently, as shown in the bottom panel of Figure 3, the distribution of delay among baseline Medical students is relatively unaffected by this experiment. After shutting down substitution into and incentives to delay within Medical programs, the reduction in total delay increases slightly to 10 percentage points. However, when there is free entry except in medical programs, the reduction in delay is evenly split between one and two years.

These experiments illustrate two important points. First, for at least some students the decision to delay is a response to the admission constraints together with the Group II GPA multiplier. However, the results suggest that these features of the admissions system generate both the incentive to delay by two years, and also a *disincentive* to delay, particularly by one year. Second, although eliminating the GPA thresholds does narrow the gap in the propensity to delay between Engineers and Humanities, it does not substantially change the pattern of delay across fields of study. In the baseline case, humanities students are 2.43 times more likely to delay than engineers. In the free entry experiment, that gap decreases to 1.7 if the ratio is calculated using the baseline field of study and 2 if using the counterfactual field of study. Taken as a whole, these experiments suggest that most of the different propensities to delay across fields of study can not be accounted for by students who delay in order to gain admissions to a preferred program.

6.6 The Value of Delay and Field of Study

We use the model to calculate an estimated 'value of delay' conditional on field of study. First, we simulate the set of choices and calculate the utility associated with those outcomes. Next, we calculate the utility delayers would have achieved if they had entered the same program but without delay. The 'value of delay' is the difference between the former and latter utilities. The values reported in the first row of Table 7 correspond to the amount of money in real DKK one would need to pay a one-year delayer to make them indifferent between delaying and entering directly, holding their program constant. The analogous figure for those who delayed by two years is reported in the first line of the second panel. The average post-schooling lifetime earnings among those who did not delay is reported at the bottom of the Table for comparison. The standard errors are constructed by performing the simulation 200 times with a different parameter vector randomly drawn from the estimated parameter distribution.

By comparing the 'total value' across fields of study, reported in the first rows of each panel, large differences are immediately apparent. The 'program-constant' total value among Humanities graduates of delaying by two years is more than triple that among Engineering graduates and for one year the difference is almost as large. While the estimated value of delaying among graduates of the other fields of study fall between those extremes, the total value among graduates of Social Science and Medical programs are somewhat lower. Because our estimates are conditional on the students' programs of study, these values of delay do not include any of the option value associated with applying under Group II. Medical and Law programs (which fall within Social Sciences) consistently have the highest GPA thresholds, thus, when we condition on having entered those programs, on average, these students require less compensation to enter without delay.

We also decompose the utility students would lose if they entered their university program without delay into factors that are either unobserved or observed in data. The observed sources of utility are further decomposed into that associated with lifetime post-schooling earnings, earnings during the year of delay, earnings during schooling, and years to degree completion.

The key reason that Ben-Porath type models predict that human capital investments will occur continuously, and early in one's life-cycle, is that interruptions imply fewer post-schooling years over which the returns to schooling will accrue. Even so, if delaying makes students more productive during school, or allows for a better match in field of study, then these factors could compensate for the lack of post-schooling experience. On balance, however, our estimates suggest that, for all but Engineering graduates, the contribution of lifetime earnings to the value of delay, reported in the fourth row in both panels of Table 7, represents a net loss of utility. The estimated loss of earnings from one year of delay ranges from 654,800 among Medical graduates to 106,400 Dkk among Engineers, which represents roughly 5 and less than 1 percent of the lifetime earnings, respectively, of individuals who had not delayed.

As one would expect, the average earnings loses associated with two years of delay are generally larger, particularly for those in the Social Sciences, which lead to occupations in law and economics with high returns to experience. In contrast, however, Engineering graduates who delay by two years experience higher earnings relative to what they would have earned without delay.

While differences across field of study in lost earnings, at least in theory, might explain the different propensities to delay, the results in Table 7 do not support that idea. Humanities graduates, who as a group are far more likely than graduates of any another field to delay by two years, lose levels of earnings are similar to delayers in Natural and Social Sciences. At the other extreme, Engineering graduates are least likely to delay and have on average higher earnings after delaying two years.

Differences in earnings during schooling and years of delay are also not large enough to account for the different propensities to delay across fields of study. Although the majority of Danish university students work while studying, average earnings in the first year of delay are twice as large as during the first year of school (not shown in table). Students who delay also have on average higher earnings during schooling. This likely reflects returns to experience, because students who delay accumulate more work hours, on average, than their counterparts who did not delay. There is no evidence, however, that delaying students have different types of jobs during school. The vast majority of sample members' pre-graduation jobs are classified as 'unskilled' and fall under the occupational code of 'unclassified'. These are also the same types of occupations held during the gap years.

Although the higher earnings during delay and schooling is a benefit of delaying, these gains do not offset the losses experienced in post-schooling earnings. A finding which is in line with Holmlund et al. (2008). Our estimates of net lost earnings are, however, much larger than Holmlund et al. (2008), who report that two years of delay is associated with a loss of lifetime earnings that is roughly half of annual earnings at age 40. The analogous figure based on our estimates is closer to two times age-40 annual earnings. One key reason that our estimates are larger is that Holmlund et al. (2008) assume that earnings among delayers catch up to non-delayers by age-40. We project earnings beyond 10 post-schooling years based on experience accumulated within those years. Thus, if delayers have not caught up within those first ten years after graduation the gap in earnings will persist.[20] Even though our estimates of earnings

[20]We report average differences in post schooling experience, which are not statistically significant, by years of

losses are large, the results also imply that policies constraining students' ability to delay, without affecting field of study, would result in welfare losses substantially larger than the additional 2 years of earnings which might be gained over the lifetime of a student.

Table 7 also reports the utility associated with the duration of students' Candidatures. If students who delay are faster or slower in completing the same program than they would have been without delay, the impact on their utility is reported in the seventh row of both panels in Table 7. The effects vary across fields. Notably, Humanities students who delay finish faster while Medical students take longer. Because the coefficient for duration of studies is -.3, the impact on utility can be large, even for relatively small changes in duration. Indeed, for Humanities students who delay by two years, the benefit associated with finishing sooner is almost as large as the loss in earnings. Could these offsetting effects be a candidate explanation for the high propensity to delay among Humanities? Although Engineering students, who delay by two years, gain relatively little from completing their degrees more quickly, their post-schooling earnings are higher as a result of delaying. Thus, combined, utility from earnings and duration of studies would suggest Engineers are more likely to delay than Humanities.

Adding together all the sources of utility that can be attributed to observed characteristics reveals that, on average, these amount to net costs for graduates of all fields. Again the net utilities suggest that, if anything, Engineers would be more likely to delay by two years. Among those that delay by one year, the net utility from observed characteristics is very similar for graduates of Engineering and Humanities.

Instead, the differences in the value of delay across fields of study are driven by unobserved factors. Although including type-heterogeneity in the model empirically improves the model fit, it is the field-delay specific intercepts that are essential to matching the distribution of delay across fields of study. [21] These intercepts allow the average utility, holding observed program

delay in a supplemental appendix.

[21] Estimated coefficients and figures showing simulated distributions of delay by field of study using estimates

characteristics constant, to differ across the interaction between fields of study and years of delay. Without them, and without type heterogeneity, the model under predicts delaying but more importantly is completely unable to match the different propensities to delay across fields. Interestingly, eliminating these intercepts does not change the conclusion that the value of delay is driven by unobserved factors. Instead, the variance of the idiosyncratic shocks is substantially larger, but because these shocks are iid they can not replicate differences in the distribution of delay across fields.

7 Conclusion

Using administrative data, we demonstrate that the common practice of delaying university among Danish students is strongly related to the decision to pursue a particular field of study. Using a dynamic discrete choice model that incorporates the university admissions policy environment active during our sample period, we estimate the value of delay conditional on the chosen field of study. A goal of this exercise is to uncover what factors might explain the different propensities to delay across fields of study. Even though the model fits the data well, our analysis reveals that differences in earnings, either post-schooling, during delay or during schooling, imply a distribution of delay that is at odds with the data. In other words, if differences in earnings were the primary reason that students delay then Engineers should be most rather than least likely to delay. This is particularly relevant because earnings should reflect many of the possible reasons that students delay. For example, if students gain valuable work experience, or make a better program match. Although these and other similar factors certainly could play a role, the estimates from our model suggest they are not important enough to explain the very large differences in delaying we observe across fields of study.

from models without type heterogeneity and field-delay specific intercepts are reported in a supplemental appendix.

We also use our model to manipulate the minimum GPA required for acceptance into different programs. Because the admissions system during our sample period rewarded individuals with work experience, there was a strategic incentive to delay in order to gain admission to high demand programs. In our simulations, we find that students do respond to the incentives inherent in the admissions system. Yet, even when all barriers to admissions are removed delaying still persists. Indeed, delay is reduced by only one-fifth. Moreover, the gap in the propensity to delay, between the most and least likely fields of study, narrows by less than a third.

Structural models frequently find that most of the variation in schooling choices can be attributed to what Heckman and co-authors call 'psychic costs' (See, for example, Carneiro et al., 2003; Cunha et al., 2005). Moreover, Arcidiacono (2004) finds that the sorting into field of study, while substantial, is not explained by monetary returns. Instead, it is preferences for particular college majors in school and in subsequent careers that drive the ability sorting observed in data. Of these two types of preferences, those while in-school are more important. To the extent that the unobserved components in our model can be interpreted as preferences, our results suggest an important link between these preferences for different fields of study and the timing of human capital.

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8 Tables and Figures

Table 1: Sample means by Field of Study (Standard Errors in Parenthesis)

	Total	Field of Study: Humanities	Nat. Sci	Soc. Sci	Eng.	Med.
Years of delay						
0 years delay	0.557	0.304	0.564	0.518	0.732	0.449
	(0.005)	(0.017)	(0.013)	(0.008)	(0.009)	(0.015)
1 year delay	0.307	0.396	0.306	0.332	0.213	0.381
	(0.005)	(0.018)	(0.012)	(0.008)	(0.008)	(0.015)
2 year delay	0.136	0.300	0.130	0.150	0.055	0.170
	(0.003)	(0.017)	(0.009)	(0.006)	(0.004)	(0.011)
Female	0.349	0.650	0.342	0.378	0.131	0.562
	(0.005)	(0.017)	(0.013)	(0.008)	(0.007)	(0.015)
High school exam grades	8.883	8.943	8.949	8.758	8.752	9.499
	(0.008)	(0.029)	(0.022)	(0.013)	(0.016)	(0.016)
Age at high school graduation	18.121	18.125	18.121	18.139	18.134	18.025
	(0.006)	(0.024)	(0.017)	(0.010)	(0.012)	(0.017)
Language line	0.200	0.705	0.029	0.313	0.005	0.132
	(0.004)	(0.017)	(0.005)	(0.007)	(0.001)	(0.010)
Number of years to completion of Candidature	6.761	7.729	7.360	6.536	6.047	7.810
	(0.008)	(0.018)	(0.010)	(0.009)	(0.009)	(0.007)
Expected PV of Lifetime Earnings (10 million DKK)	1.361	0.859	1.213	1.433	1.549	1.203
	(0.004)	(0.008)	(0.007)	(0.006)	(0.004)	(0.005)
PV Student grants (10 million DKK)	0.013	0.017	0.015	0.011	0.011	0.016
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
PV Earnings during university (10 million DKK)	0.042	0.036	0.038	0.049	0.032	0.053
	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)
Program located in own region	0.434	0.420	0.454	0.482	0.359	0.428
	(0.005)	(0.018)	(0.013)	(0.008)	(0.009)	(0.015)
Program located in own city	0.123	0.169	0.152	0.133	0.073	0.138
	(0.003)	(0.014)	(0.010)	(0.005)	(0.005)	(0.010)
Mother holds Candidature in same field of study	0.015	0.026	0.004	0.016	0.006	0.042
	(0.001)	(0.006)	(0.002)	(0.002)	(0.001)	(0.006)
Father holds Candidature in same field of study	0.074	0.071	0.012	0.067	0.094	0.127
	(0.003)	(0.009)	(0.003)	(0.004)	(0.006)	(0.010)
% of High school peers entering own field of study	0.083	0.059	0.052	0.123	0.064	0.041
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
% of High school study line entering field of study	0.652	0.449	0.786	0.490	0.885	0.639
	(0.002)	(0.005)	(0.003)	(0.002)	(0.001)	(0.006)
Own GPA deviation from program threshold	1.270	1.220	1.874	0.952	1.901	0.188
	(0.012)	(0.042)	(0.033)	(0.016)	(0.023)	(0.015)
Year of high school graduation						
1981	0.217	0.252	0.218	0.204	0.223	0.225
	(0.004)	(0.016)	(0.011)	(0.006)	(0.008)	(0.013)
1982	0.243	0.275	0.224	0.244	0.225	0.282
	(0.004)	(0.016)	(0.011)	(0.007)	(0.008)	(0.014)
1983	0.259	0.238	0.271	0.264	0.254	0.252
	(0.004)	(0.015)	(0.012)	(0.007)	(0.009)	(0.013)
1984	0.281	0.235	0.287	0.288	0.298	0.241
	(0.005)	(0.015)	(0.012)	(0.007)	(0.009)	(0.013)
Sample Size	9,670	757	1,364	3,851	2,589	1,109

Table 2: Sample means by years of delay (Standard Errors in Parenthesis)

	# Years of delay		
	0 years	1 year	2 years
Female	0.277	0.427	0.470
	(0.006)	(0.009)	(0.014)
High school exam grades	8.971	8.811	8.683
	(0.011)	(0.015)	(0.021)
Age at high school graduation	18.110	18.141	18.117
	(0.008)	(0.011)	(0.017)
Language line	0.144	0.245	0.330
	(0.005)	(0.008)	(0.013)
Number of years to completion of Candidature	6.668	6.846	6.952
	(0.010)	(0.016)	(0.025)
Expected PV of Lifetime Earnings (10 million DKK)	1.446	1.290	1.177
	(0.004)	(0.007)	(0.011)
Earnings during first year of delay (10 million DKK)		0.005	0.005
		(0.000)	(0.000)
Earnings during second year of delay (10 million DKK)			0.010
			(0.000)
PV Student grants (10 million DKK)	0.011	0.014	0.016
	(0.000)	(0.000)	(0.000)
PV Earnings during university (10 million DKK)	0.038	0.045	0.054
	(0.000)	(0.000)	(0.001)
Program located in own region	0.456	0.421	0.376
	(0.007)	(0.009)	(0.013)
Program located in own city	0.124	0.128	0.105
	(0.004)	(0.006)	(0.008)
Mother holds Candidature in same field of study	0.016	0.016	0.012
	(0.002)	(0.002)	(0.003)
Father holds Candidature in same field of study	0.077	0.072	0.062
	(0.004)	(0.005)	(0.007)
% of High school peers entering own field of study	0.083	0.084	0.082
	(0.001)	(0.001)	(0.001)
% of High school study line entering field of study	0.692	0.618	0.561
	(0.003)	(0.004)	(0.006)
Own GPA deviation from program threshold	1.478	1.078	0.850
	(0.016)	(0.022)	(0.035)
Year of high school graduation			
1981	0.227	0.206	0.202
	(0.006)	(0.007)	(0.011)
1982	0.256	0.226	0.228
	(0.006)	(0.008)	(0.012)
1983	0.257	0.268	0.248
	(0.006)	(0.008)	(0.012)
1984	0.261	0.299	0.322
	(0.006)	(0.008)	(0.013)
Sample Size	5,386	2,970	1,314

Table 3: Sample Fields of Study, Faculties and Universities

	Faculties				
Universities	Humanites	Natural Sciences	Social Sciences	Engineering	Medicine
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 4: GPA Thresholds From the KOT

	Group I				
	Humanities	Nat. Sci	Soc. Sci	Eng.	Med.
Mean	7.11	7.21	7.6	7.17	9.35
Standard Deviation	1.16	1.21	1.21	1.12	0.26
Minimum	6	6	6	6	8.8
Maximum	9.1	9.1	9.4	9	9.7
	Group II				
	Humanities	Nat. Sci	Soc. Sci	Eng.	Med.
Mean	6.5	6.64	6.75	6.11	8.5
Standard Deviation	0.73	0.96	0.98	0.32	0.34
Minimum	6	6	6	6	7.8
Maximum	8.4	8.7	8.6	7.1	8.9

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

Table 5: Characteristics Associated With Delaying University (Standard Errors in Parenthesis)

	1 or 2 years vs. 0 years	1 year vs. 0 years	2 years vs. 1 year	Linear 0 to 2 years
Mean of dependent variable	0.443	0.355	0.307	0.579
Average high school exam grades	-0.096***	-0.074***	-0.059***	-0.148***
	(0.006)	(0.006)	(0.009)	(0.009)
% youth unemployed in city	-0.002	-0.002	0.002	-0.001
	(0.001)	(0.001)	(0.002)	(0.002)
Female	0.157***	0.151***	0.002	0.204***
	(0.013)	(0.013)	(0.019)	(0.019)
Age at high school graduate –Reference group Age 17				
Age 18	0.006	0.003	0.010	0.009
	(0.015)	(0.016)	(0.023)	(0.022)
Age 19	0.029	0.043*	-0.051	0.009
	(0.018)	(0.019)	(0.026)	(0.026)
Age 20	-0.037	-0.026	-0.014	-0.066
	(0.042)	(0.044)	(0.066)	(0.062)
Exam type–Reference group Gymnasium-Mathematics line				
Gymnasium-Language line	0.157***	0.120***	0.099***	0.258***
	(0.013)	(0.015)	(0.017)	(0.019)
Family Background				
Ln Family Income	0.032**	0.038***	-0.021	0.030
	(0.011)	(0.011)	(0.015)	(0.015)
Family structure–Reference group lone parent families				
Lived in a two parent family	-0.021	0.002	-0.072**	-0.060**
	(0.016)	(0.017)	(0.023)	(0.023)
Mother's Education –Reference group Long-Cycle				
Less than high school	-0.075**	-0.075**	0.009	-0.091**
	(0.023)	(0.024)	(0.036)	(0.033)
High school	-0.085***	-0.075***	-0.018	-0.117***
	(0.014)	(0.015)	(0.020)	(0.021)
Short-cycle education	-0.082***	-0.072***	-0.025	-0.116***
	(0.014)	(0.015)	(0.020)	(0.020)
Medium-cycle education	-0.052*	-0.046*	-0.025	-0.078*
	(0.022)	(0.024)	(0.032)	(0.032)
Mother's education data missing	-0.007	-0.024	0.033	0.015
	(0.037)	(0.041)	(0.051)	(0.053)
Father's Education –Reference group Long-Cycle				
Less than high school	0.025	0.031	-0.022	0.023
	(0.016)	(0.017)	(0.023)	(0.023)
High school	0.034*	0.036*	-0.008	0.040
	(0.017)	(0.018)	(0.024)	(0.024)
Short-cycle education	0.015	0.023	-0.035	0.004
	(0.016)	(0.016)	(0.023)	(0.022)
Medium-cycle education	0.047	0.045	0.016	0.066
	(0.029)	(0.031)	(0.042)	(0.042)
Father's education data missing	-0.005	0.021	-0.081*	-0.048
	(0.026)	(0.028)	(0.035)	(0.039)
Sample Size	9670	8356	4284	9670
Psuedo R-squared/ R-squared	0.069	0.054	0.025	0.096

Table 6: Model Estimation Results (Standard Errors in Parenthesis)

	1 Type	2 Types		1 Type	2 Types
Value of Schooling Intercepts					
Natural sciences, no delay	1.425	2.248	Social sciences, no delay	1.579	3.567
	(0.148)	(0.558)		(0.163)	(0.630)
Engineering, no delay	2.724	-1.445	Medical programs, no delay	3.242	4.922
	(0.236)	(2.131)		(0.258)	(0.699)
Humanities, 1 year delay	-0.569	0.695	Natural sciences, 1 year delay	0.001	1.822
	(0.131)	(0.413)		(0.119)	(0.685)
Social sciences, 1 year delay	0.087	2.403	Egineering, 1 year delay	0.097	-2.240
	(0.115)	(0.653)		(0.131)	(2.153)
Medical programs, 1 year delay	2.503	4.583	Humanities, 2 years delay	-1.714	0.470
	(0.217)	(0.731)		(0.213)	(0.682)
Natural sciences, 2 years delay	-1.931	0.625	Social sciences, 2 years delay	-1.672	1.075
	(0.216)	(0.748)		(0.188)	(0.676)
Engineering, 2 years delay	-2.532	-3.258	Medical programs, 2 years delay	0.007	2.532
	(0.238)	(2.229)		(0.176)	(0.711)
Value of Schooling Program Characteristics And Delay Parameters					
Expected years to completion	-0.360	-0.300	Program located in own city	0.496	0.580
	(0.038)	(0.033)		(0.072)	(0.075)
Program located in own region	2.112	1.981	Father holds degree in same field	0.982	1.058
	(0.148)	(0.132)		(0.096)	(0.112)
Mother holds degree in same field	0.427	0.355	Age (Value of delay)	-0.025	-0.054
	(0.148)	(0.159)		(0.032)	(0.030)
Preference shocks					
$\exp(\tau)$	0.272	0.139	τ	1.31	1.15
	(0.068)	(0.064)			
Type specific intercepts					
Humanties		-3.889	Natural Sciences		-5.179
		(0.720)			(1.135)
Social Sciences		-8.544	Engineering		0.270
		(1.212)			(2.220)
Medical Programs		-7.654	Delay		-1.637
		(1.356)			(0.471)
$Invnormal\,(\mathbb{P}\,[Type2])$		-0.172	$\mathbb{P}\,[Type2]$		.432
		(0.068)			
Log likelihood	-35089.47	-34911.44	Sample Size	9,670	9,670

Table 7: Utility Lost if Entering the Same Program without Delay (Standard Errors in Parenthesis)

	Humanities	Natural Sciences	Social Sciences	Engineering	Medical Programs
			One year of delay		
Total utility	5.6959	4.3468	3.2792	1.9857	3.1891
	(0.3778)	(0.2823)	(0.2294)	(0.2344)	(0.2155)
Unobserved factors	5.7634	4.5108	3.3386	2.0597	3.3607
	(0.3823)	(0.2951)	(0.2362)	(0.2382)	(0.2270)
Observed factors	-0.0675	-0.1641	-0.0594	-0.0740	-0.1716
	(0.0335)	(0.0354)	(0.0332)	(0.0330)	(0.0312)
Lifetime Earnings	-0.0554	-0.0561	-0.0169	-0.0102	-0.0654
	(0.0029)	(0.0053)	(0.0026)	(0.0027)	(0.0016)
Earnings during schooling	0.0039	0.0039	0.0049	0.0067	0.0101
	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Earnings during delay	0.0051	0.0053	0.0054	0.0054	0.0049
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Years to completion	0.0690	-0.0208	0.0388	0.0065	-0.0334
	(0.0077)	(0.0021)	(0.0042)	(0.0009)	(0.0033)
Other observed characteristics	-0.0902	-0.0964	-0.0917	-0.0823	-0.0878
	(0.0333)	(0.0333)	(0.0331)	(0.0326)	(0.0301)
			Two years of delay		
Total utility	5.8323	4.2626	2.9131	1.6048	2.8161
	(0.5224)	(0.3208)	(0.2235)	(0.4723)	(0.2087)
Unobserved factors	6.0374	4.5737	3.1875	1.7423	3.0973
	(0.5385)	(0.3477)	(0.2534)	(0.4815)	(0.2449)
Observed factors	-0.2050	-0.3111	-0.2744	-0.1375	-0.2812
	(0.0917)	(0.0932)	(0.0936)	(0.0950)	(0.0866)
Lifetime Earnings	-0.1012	-0.1002	-0.1037	0.0274	-0.0201
	(0.0036)	(0.0056)	(0.0056)	(0.0086)	(0.0041)
Earnings during schooling	0.0092	0.0143	0.0158	0.0154	0.0156
	(0.0001)	(0.0001)	(0.0002)	(0.0001)	(0.0001)
Earnings during delay	0.0162	0.0161	0.0165	0.0164	0.0149
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Years to completion	0.0958	-0.0060	0.0279	0.0060	-0.0707
	(0.0108)	(0.0011)	(0.0033)	(0.0008)	(0.0072)
Other observed characteristics	-0.2251	-0.2353	-0.2309	-0.2028	-0.2209
	(0.0927)	(0.0921)	(0.0930)	(0.0929)	(0.0853)
			Mean Post-Schooling Liftetime Earnings for Non-Delayers		
	0.9165	1.2919	1.4920	1.5689	1.2370

Notes: The utility values in the table are present value, from the point of view of a high school graduate, denominated in 10 million real DKK (year 2000). Positive values are losses relative to entering without delay, and negative values are gains. In other words, the values in the table correspond to an amount one would have to pay a student to enter without delay. The lifetime earnings are present value from the point of view of a university graduate.

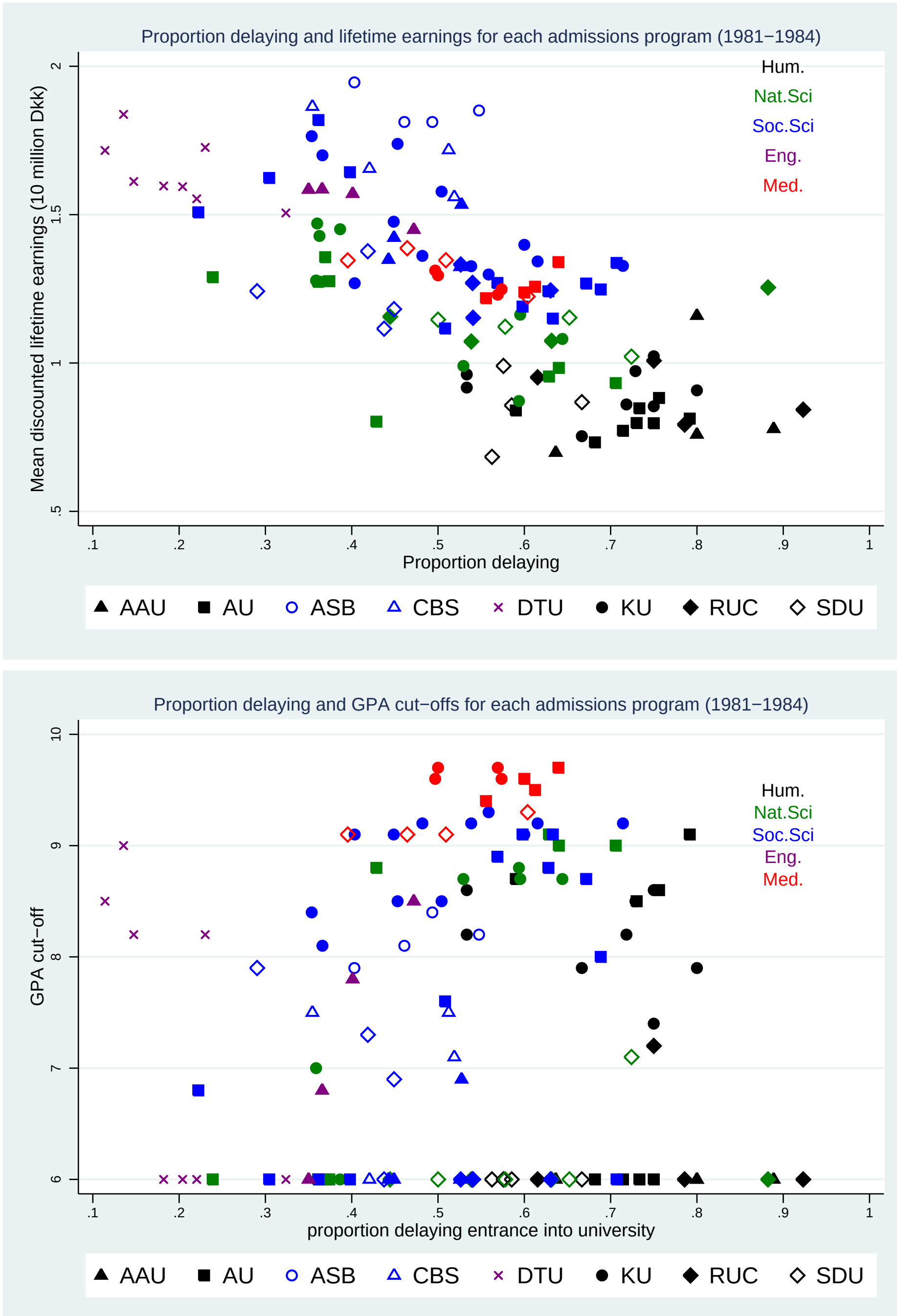

Figure 1: Correlation between Delaying and Lifetime Earnings, and Program GPA Threshold

Notes: AAU: Aalborg University, AU: Aarhus University, ASB: Aarhus School of Business, CBS: Copenhagen Business School, DTU: Danish Technical University, KU: University of Copenhagen, RUC: Roskilde University, SDU: University of Southern Denmark

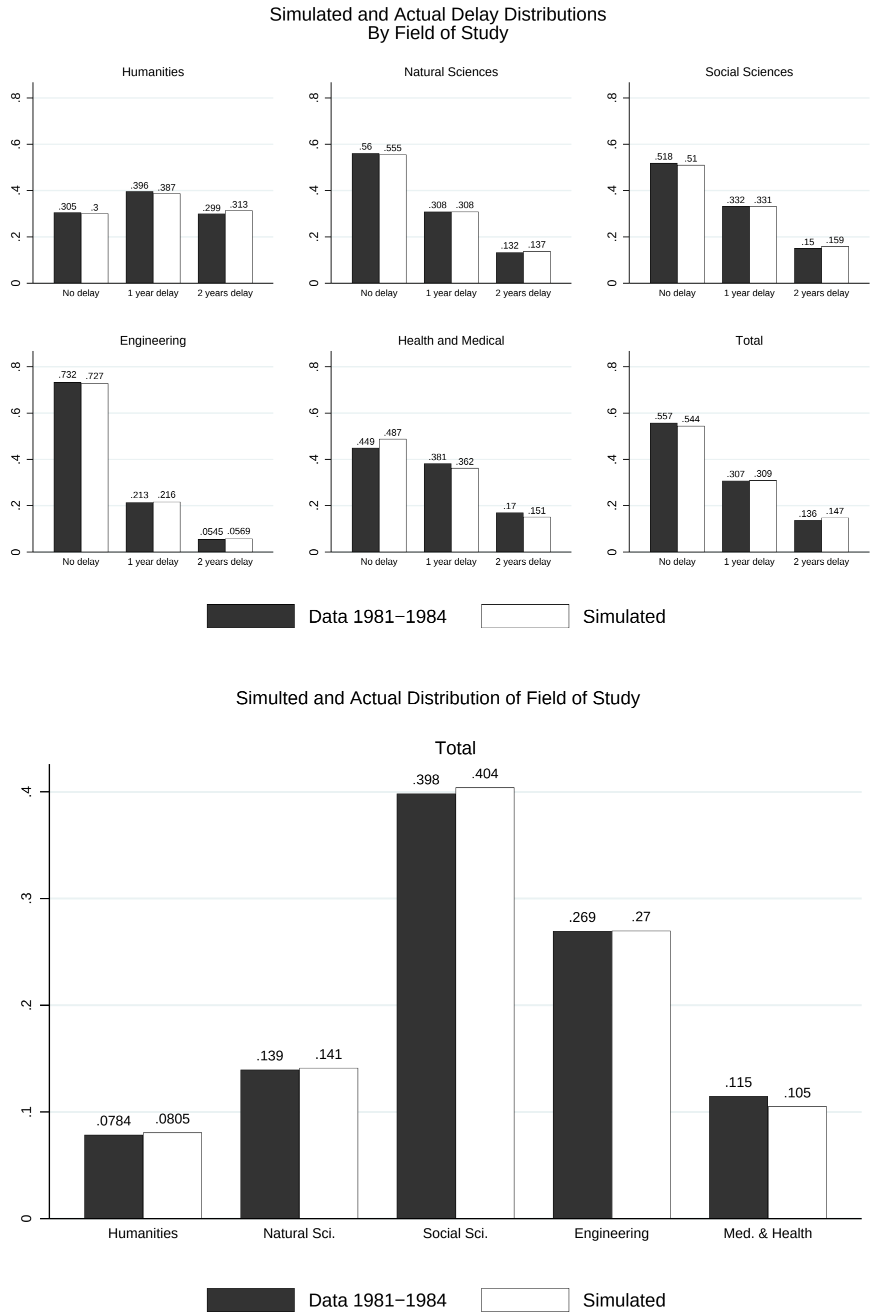

Figure 2: In Sample Model Fit, Distributions of Delay and Field of Study

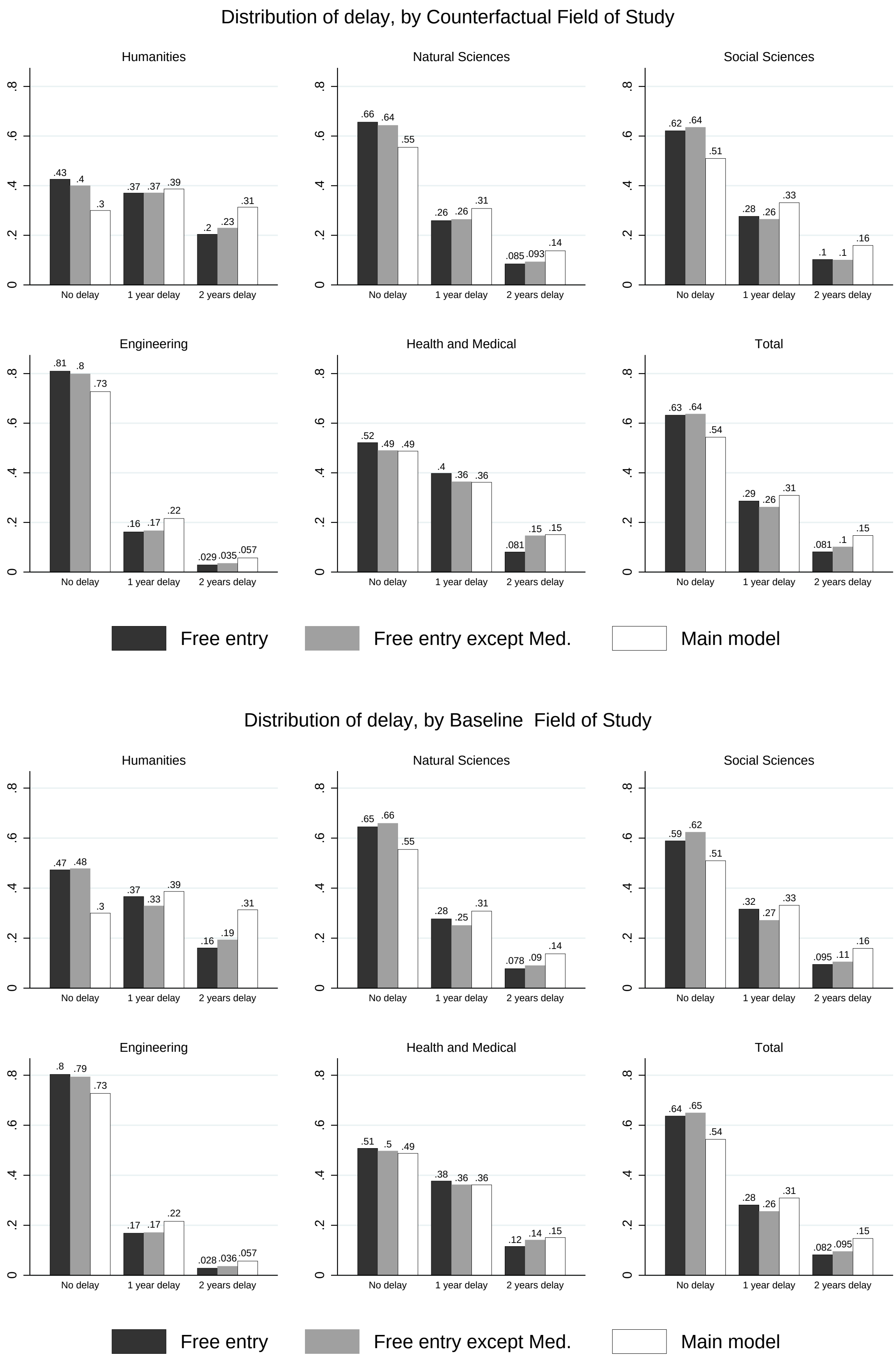

Figure 3: Counterfactual Distributions of Delay by Field of Study

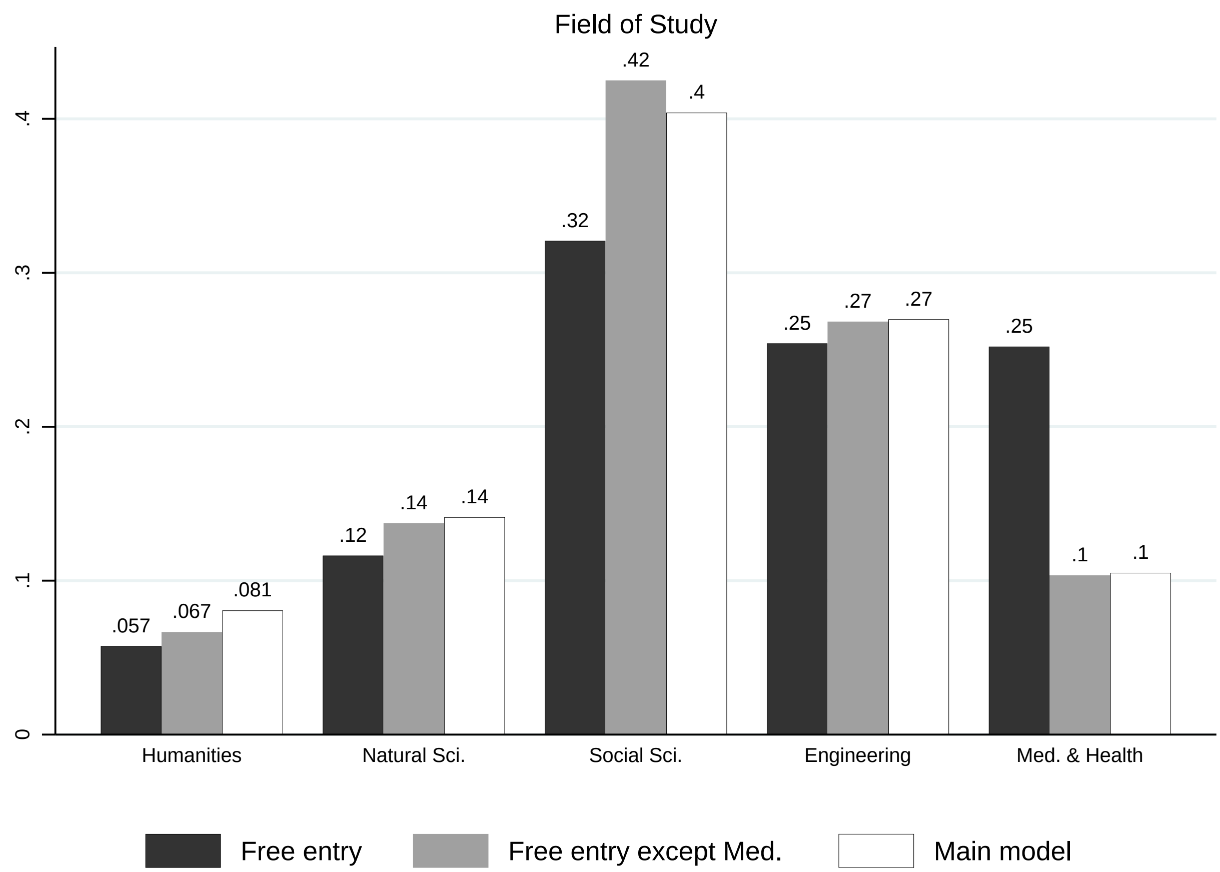

Figure 4: Counterfactual Distributions of Field of Study

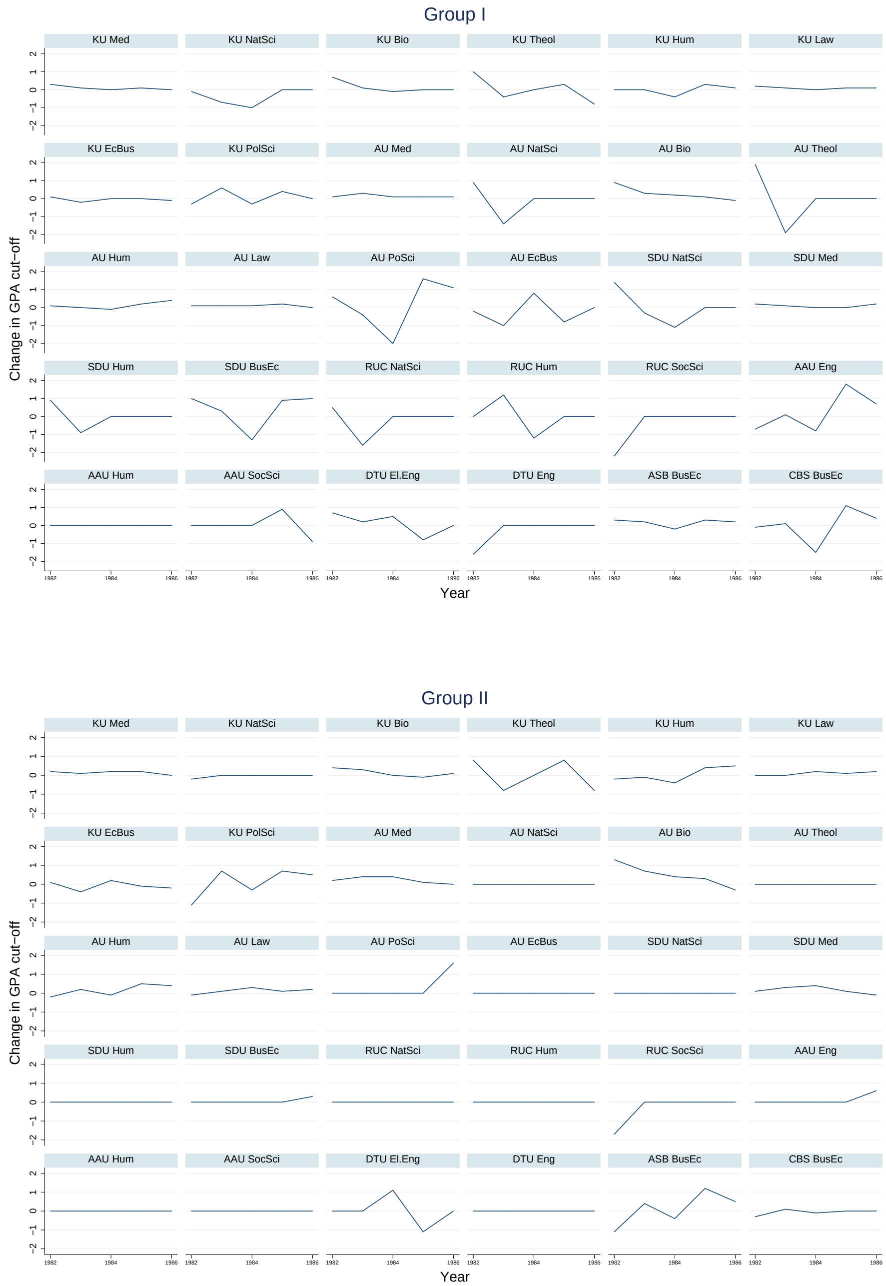

Figure 5: Changes in GPA thresholds for Group I and Group II

Notes: AAU: Aalborg University, AU: Aarhus University, ASB: Aarhus School of Business, CBS: Copenhagen Business School, DTU: Danish Technical University, KU: University of Copenhagen, RUC: Roskilde University, SDU: University of Southern Denmark

A Variable construction

Expected 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. To do this, we first estimate the returns to experience separately by gender, program and institution. We use a sample of individuals who are not included in our main sample, but who graduated from the same degree programs. This sample graduated between 1971 and 1988.[22] We know when this sample graduated from their Candidature and their age. We estimate returns to experience starting with the eleventh year post-candidature by regressing log real earnings on years since candidature and squared term, also controlling for age and cohort. Using those gender-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%.

Next, we generate expected lifetime earnings for each of the 90 unique delay-program choice paths. The expected values are estimated using the sample means conditional on gender, high school grades, high school study line (language or math) and, high school graduation age and cohort.

Expected Earnings During Delay

Expected earnings during each year of delay are the mean earnings in the sample conditional on gender, age at high school graduation, high school GPA, the high school curriculum focus (i.e. either mathematics or language), the city in which the student lived, and the students' high school graduation cohort.

[22]This sample is not included in the main analysis because their high school grades and high school graduation dates are not included in the registers.

Expected Earnings During Schooling

For each observation, we calculate the present value of earnings during schooling by summing total annual earnings, discounted by 4%, from the first year to final year of schooling. We then estimate expected earnings by using the mean earnings within each of the 90 delay-university-program cells conditional on the same set of variables used to estimate expected earnings during delay.

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 which 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. For example, a student who entered a Humanities program directly from high school and received 10,000 DKK per year, would also expect to receive 10,000 DKK per year if she had entered any of the other programs without delay.

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.

Expected Years to Graduation

The expected number of years taken to graduate from a Candidature is the sample mean within cells defined by an interaction between gender, field of study and years of delay.

B Supplemental appendices

B.1 Labour force status during delay and reduced form effects of delaying

Table 8: Labour force activity during delay (Standard Errors in Parenthesis)

	Full Sample	Humanities	Natural Sciences	Field of Study Social Sciences	Engineering	Med. and Health
				One Year of Delay		
Unemployed	0.080***	0.129***	0.119***	0.070***	0.073***	0.054***
	(0.005)	(0.017)	(0.015)	(0.007)	(0.010)	(0.009)
Employed	0.647***	0.472***	0.638***	0.666***	0.721***	0.641***
	(0.008)	(0.025)	(0.023)	(0.012)	(0.017)	(0.019)
Not in labour force	0.048***	0.068***	0.040***	0.048***	0.047***	0.041***
	(0.004)	(0.012)	(0.009)	(0.006)	(0.008)	(0.008)
Student	0.027***	0.071***	0.044***	0.021***	0.014**	0.015**
	(0.003)	(0.013)	(0.010)	(0.004)	(0.004)	(0.005)
Employed in Skilled Work	0.057***	0.049***	0.049***	0.051***	0.047***	0.090***
	(0.004)	(0.011)	(0.010)	(0.006)	(0.008)	(0.011)
Hours worked	355.159***	228.667***	348.663***	380.179***	397.301***	339.363***
	(5.244)	(13.679)	(14.721)	(8.588)	(11.807)	(12.055)
Sample Size	3,648	411	453	1,431	699	654
				Two Years of Delay- First Year		
Unemployed	0.093***	0.139***	0.087***	0.097***	0.078***	0.054***
	(0.007)	(0.020)	(0.020)	(0.011)	(0.018)	(0.013)
Employed	0.617***	0.455***	0.614***	0.643***	0.693***	0.666***
	(0.012)	(0.029)	(0.034)	(0.018)	(0.031)	(0.027)
Not in labour force	0.052***	0.069***	0.058***	0.050***	0.046**	0.037***
	(0.005)	(0.015)	(0.016)	(0.008)	(0.014)	(0.011)
Student	0.046***	0.073***	0.077***	0.031***	0.028*	0.047***
	(0.005)	(0.015)	(0.019)	(0.006)	(0.011)	(0.012)
Employed in Skilled Work	0.085***	0.056***	0.116***	0.092***	0.078***	0.081***
	(0.007)	(0.013)	(0.022)	(0.011)	(0.018)	(0.016)
Hours worked	333.282***	211.867***	329.777***	372.632***	367.119***	340.182***
	(7.436)	(14.078)	(20.155)	(12.002)	(20.838)	(19.071)
Sample Size	1,738	303	207	714	218	296
				Two Years of Delay- Second Year		
Unemployed	0.092***	0.128***	0.078***	0.098***	0.096***	0.049***
	(0.007)	(0.019)	(0.019)	(0.011)	(0.020)	(0.013)
Employed	0.699***	0.574***	0.761***	0.710***	0.706***	0.756***
	(0.011)	(0.029)	(0.030)	(0.017)	(0.031)	(0.026)
Not in labour force	0.071***	0.054***	0.093***	0.068***	0.096***	0.064***
	(0.006)	(0.013)	(0.020)	(0.009)	(0.020)	(0.015)
Student	0.049***	0.097***	0.054***	0.040***	0.037**	0.028**
	(0.005)	(0.017)	(0.016)	(0.007)	(0.013)	(0.010)
Employed in Skilled Work	0.172***	0.087***	0.200***	0.176***	0.225***	0.191***
	(0.009)	(0.016)	(0.028)	(0.014)	(0.028)	(0.023)
Hours worked	924.107***	612.507***	947.503***	995.605***	1054.660***	956.345***
	(14.564)	(31.098)	(40.524)	(22.536)	(38.585)	(36.397)
Sample Size	1,710	298	205	706	218	283

Table 9: Differences in Earnings in First 10 Post-Schooling Years 10 million DKK (Standard Errors in Parenthesis)

	(1)	(2)	(3)	(4)
Years of delay –Reference group no delay				
One year	-1.053**	-0.396	-0.715*	
	(0.340)	(0.341)	(0.338)	
Two years	-1.217**	-0.024	-0.210	
	(0.459)	(0.464)	(0.462)	
High school exam grades		0.992***	0.714***	0.736***
		(0.192)	(0.198)	(0.198)
Exam type–Reference group Gymnasium-Mathematics line				
Gymnasium-Language line		-4.913***	-4.828***	-4.796***
		(0.382)	(0.423)	(0.423)
Faculty –Reference group Humanities				
Natural Sciences			1.190	
			(0.724)	
Social Sciences			7.669***	
			(0.621)	
Engineering			4.346***	
			(0.707)	
Health Related			10.563***	
			(0.731)	
Years of delay Interacted with Faculty				
Reference group no delay in Humanities				
One year				0.508
				(1.260)
Two years				1.003
				(1.348)
Reference group no delay in Natural Sciences				
One year				-3.112***
				(0.905)
Two years				-2.794*
				(1.244)
Reference group no delay in Social Sciences				
One year				-1.198*
				(0.510)
Two years				-1.179
				(0.670)
Reference group no delay in Engineering				
One year				-0.377
				(0.685)
Two years				1.925
				(1.231)
Reference group no delay in Health Related				
One year				2.292*
				(0.944)
Two years				3.032*
				(1.228)
Sample Size	9,670	9,670	9,670	9,670
R-squared	0.026	0.044	0.088	0.090

All specification include controls for an interaction in age at high school graduation and years of candidature, family background, year of high school graduation, and region of the country

Table 10: Differences in Present Value Earnings Projected to Age 60 10 million DKK (Standard Errors in Parenthesis)

	(1)	(2)	(3)	(4)
Years of delay –Reference group no delay				
One year	-0.135***	-0.105***	-0.081***	
	(0.017)	(0.017)	(0.017)	
Two years	-0.223***	-0.172***	-0.127***	
	(0.023)	(0.024)	(0.024)	
High school exam grades		-0.002	0.025*	0.026*
		(0.010)	(0.010)	(0.010)
Exam type–Reference group Gymnasium-Mathematics line				
Gymnasium-Language line		-0.274***	-0.249***	-0.248***
		(0.020)	(0.022)	(0.022)
Faculty –Reference group Humanities				
Natural Sciences			0.128***	
			(0.037)	
Social Sciences			0.375***	
			(0.032)	
Engineering			0.375***	
			(0.037)	
Health Related			0.191***	
			(0.037)	
Years of delay Interacted with Faculty				
Reference group no delay in Humanities				
One year				-0.049
				(0.066)
Two years				-0.092
				(0.070)
Reference group no delay in Natural Sciences				
One year				-0.159***
				(0.047)
Two years				-0.211**
				(0.064)
Reference group no delay in Social Sciences				
One year				-0.080**
				(0.026)
Two years				-0.179***
				(0.034)
Reference group no delay in Engineering				
One year				-0.080*
				(0.036)
Two years				-0.026
				(0.066)
Reference group no delay in Health Related				
One year				-0.020
				(0.048)
Two years				0.031
				(0.063)
Sample Size	9,670	9,670	9,670	9,670
R-squared	0.074	0.096	0.118	0.120

All specification include controls for an interaction in age at high school graduation and years of candidature, family background, year of high school graduation, and region of the country

Table 11: Differences in Post-Schooling Years of Experience (Standard Errors in Parenthesis)

	(1)	(2)	(3)	(4)
Years of delay –Reference group no delay				
One year	-0.026	0.023	-0.010	
	(0.059)	(0.060)	(0.060)	
Two years	-0.087	0.003	-0.041	
	(0.080)	(0.081)	(0.082)	
High school exam grades		0.161***	0.051	0.051
		(0.034)	(0.035)	(0.035)
Exam type–Reference group Gymnasium-Mathematics line				
Gymnasium-Language line		-0.224***	-0.071	-0.069
		(0.067)	(0.075)	(0.075)
Faculty –Reference group Humanities				
Natural Sciences			-0.205	
			(0.128)	
Social Sciences			-0.262*	
			(0.110)	
Engineering			0.051	
			(0.125)	
Health Related			0.883***	
			(0.130)	
Years of delay Interacted with Faculty				
Reference group no delay in Humanities				
One year				-0.073
				(0.224)
Two years				0.229
				(0.241)
Reference group no delay in Natural Sciences				
One year				-0.115
				(0.161)
Two years				-0.370
				(0.220)
Reference group no delay in Social Sciences				
One year				-0.003
				(0.091)
Two years				-0.034
				(0.119)
Reference group no delay in Engineering				
One year				0.051
				(0.122)
Two years				-0.171
				(0.220)
Reference group no delay in Health Related				
One year				0.060
				(0.168)
Two years				0.071
				(0.219)
Sample Size	10,004	10,004	10,004	10,004
R-squared	0.010	0.013	0.028	0.028

All specification include controls for an interaction in age at high school graduation and years of candidature, family background, year of high school graduation, and region of the country

B.2 Out of sample model fit

Because there is a strong upward trend in delaying, it is not possible to match the level of delay out of the sample. However, here we present how well the main model (with type-heterogeneity) matches the ratio of delay among Humanities to the reported field of study. The column marked 1981-1984 is the data used in estimation, while the data marked 1987-1989 was not.

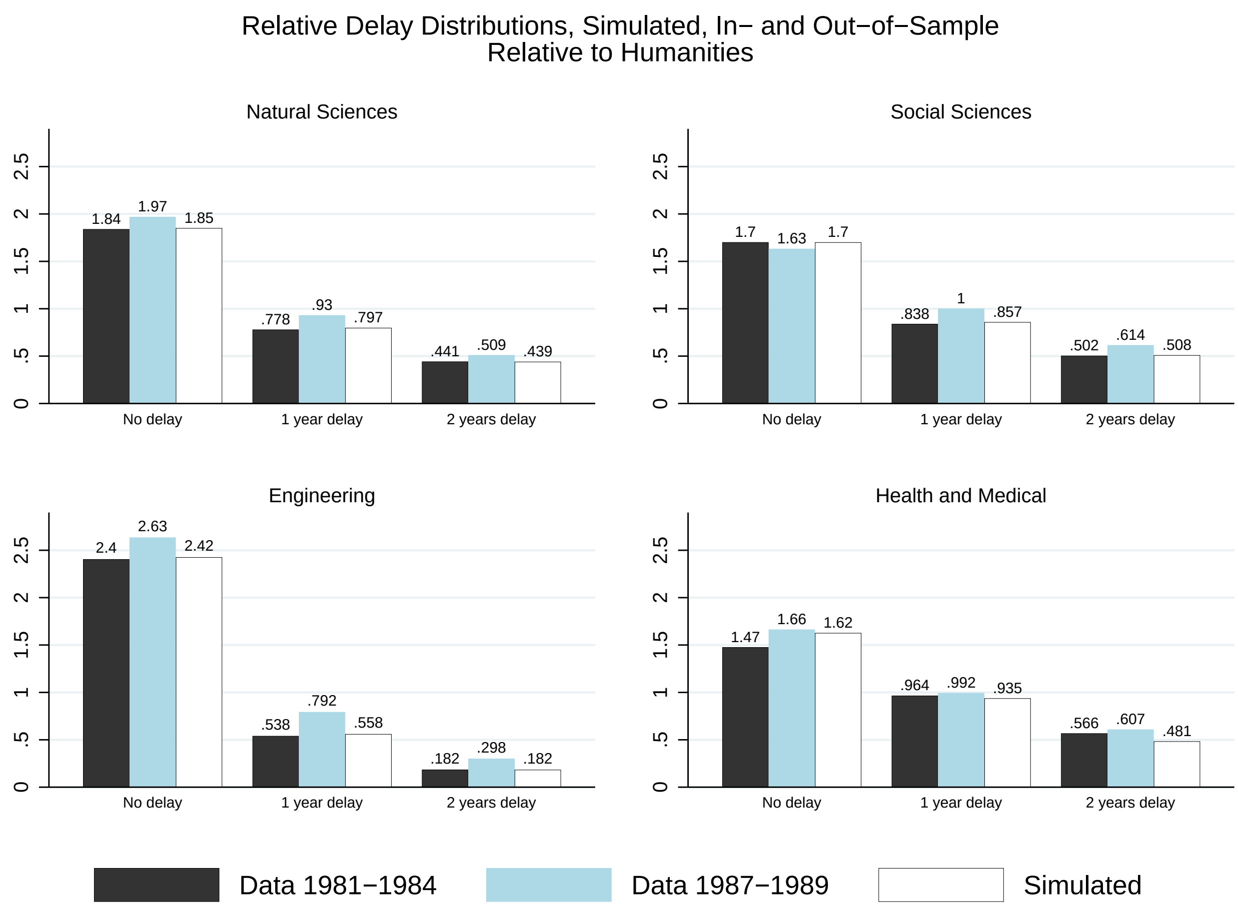

Figure 6: Out of sample model fit

B.3 Models without Type Heterogeneity and Delay-Field Specific Intercepts

The following figure presents the delay distributions simulated in the model with type heterogeneity reported in the first column of Table 6

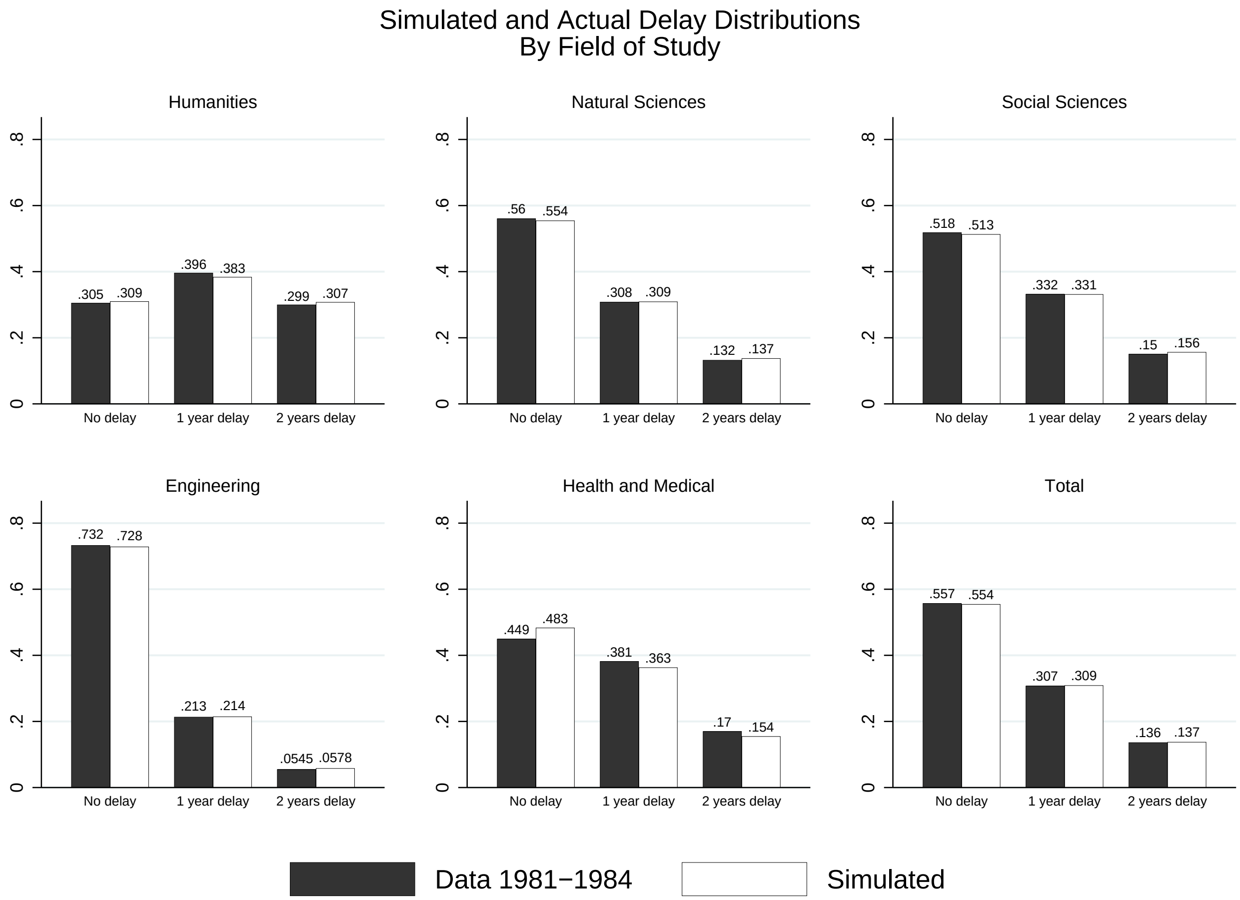

Figure 7: Fit from model without type or delay-field specific intercepts

Here, we report how well a model without type heterogeneity and where the field of study intercepts do not differ by years of delay.

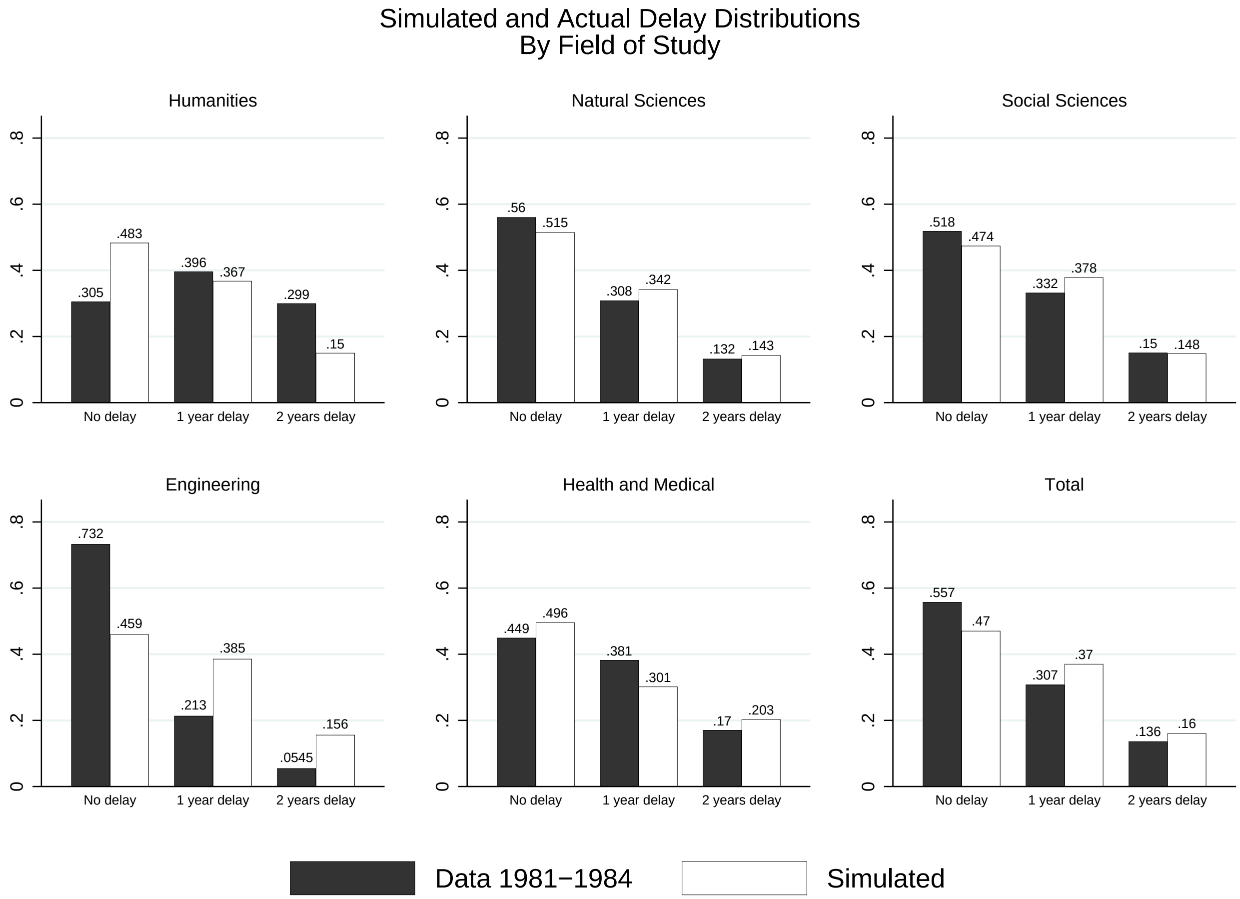

Figure 8: Fit from model without type or delay-field specific intercepts