Admissions Constraints and the Decision to Delay University
Online Appendices

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Abstract

We investigate whether delaying entrance into university is affected by restrictions on admissions into competitive programs. Using Danish administrative data, we estimate a dynamic discrete choice model, in which students choose, if admitted, whether to enter one of 30 programs or delay. We use the model to examine delaying choices under different simulated admissions policies. Our experiments suggest that only 28% of students who delay do so because of admissions restrictions. Furthermore, although students respond to admissions incentives, our results imply that such policies are unlikely to substantially change the overall distribution of delay.

Keywords: University admissions policies; Timing of university enrollment
JEL Classification: I2;J24

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This research was supported by a grant from the Danish Research Council. The authors are grateful for helpful comments from Nicole Fortin, David Green, Oskar Nordström Skans, Andreas Pollak, Ben Sand, members of The Centre for Applied Microeconometrics, The Copenhagen Education Network and The Canadian Labour Economics Forum.

A Variable construction

Observed Characteristics in the Utility of Schooling

The instantaneous utility experienced from a program depends on a set of program characteristics. These include the student to teacher ratio, indicators for whether one's mother or father completed a degree in the same field of study, whether the program is located in the same municipality or the same region as the student, and whether the program matches one's own gender and high school track.

The student-teacher ratio varies by university and field of study and is taken from the historical financial records of the yearly Danish Finance Acts during the period.[1]

A program matches one's gender or high school track if the majority of students entering that field of study have the same gender or track, respectively. We calculate the fraction in each field of study using the whole sample period, but the shares are fairly stable across the sample period. Humanities and Medicine are coded as "female" fields of study, and Natural Sciences, Engineering, and Medicine are coded as "Math" track fields.

The utility of a program includes an indicator that equals 1 if a student's mother or female guardian holds a bachelors degree in the same field of study as the program, and equals zero otherwise. Cases where the student does not have a mother registered or the mother did not complete any long-cycle education are coded as zero. There is also an analogous indicator for whether the student's father completed a degree in the program's field of study.

To construct indicators for whether a program is located in the same municipality or region we use the address of the student in the year she graduated from high school. A "region" is defined by the first digit of the municipality code which corresponds to a slightly aggregated version of the administrative regions for, among other, High Schools and hospitals during the period.

Expected Lifetime Earnings in Schooling

Within a period, students' decisions to enter a particular field of study depend on the expected present value of lifetime income. In this appendix sub-section, we describe, first, how we construct lifetime income, and then, how we estimate expected income.

Annual income is defined as the total employment income from all employers as reported to the tax authority. The first year of students' lifetime incomes is the calendar year they enter a given program. We observe the full sample for 23 years following their first year of university. Because students enter university at different ages, the 23rd year corresponds to ages ranging from 40 to 45. For all sample members, we project future earnings out to age 60 using the individuals' average earnings across the last three observed years (21-23 years after entering university). We then assume that individuals earn that amount in every year until age 60. This will tend to over-estimate earnings among individuals who retire early and under-estimate earnings among those who either experience continued wage growth or retire later.

Using the actual earnings in the first 23 years and the earnings projected out to age 60, we calculate the discounted present value using a discount rate of 4 percent. The lifetime income measure is expressed in millions of real Danish kroner (indexed to the year 2000).

[1]Reference: Finance Act (Forslag til Finanslov), 1981, (from § 20, nr. 8, Højere og Videregående uddannelse, Anmærkninger 2, S. 824-915.)

At the moment students are choosing which program to enter, they do not know how much income they will earn in any of the programs. Instead, we assume that they form expectations about their future incomes in all of the programs. Specifically, we assume that expected future earnings for program p after g years of delay are a linear function of a set of observed characteristics (x_i):

$$\mathbb{E}\left[PV\ earn_{ipg}|x_i\right]_{pg} = x_i\beta_{pg} \tag{A.1}$$

To estimate these expected lifetime incomes, we predict conditional sample averages. Specifically, in the sub-sample that entered program p after g years of delay, we regress the observed present value lifetime earnings on the vector of characteristics to obtain the estimate β_{gp}. We then use the β_{gp} vector to generate a predicted lifetime earnings for each observation in each path:

$$\widehat{PV\ earn}_{ipg} = x_i\hat{\beta}_{pg} \tag{A.2}$$

The predicted lifetime earnings is for all sample members creating an estimated counterfactual expected earnings in all program and delay combinations. $\widehat{PV\ earn}_{ipg}$ varies across the program and delay choices because the predicted returns to an individual's characteristics vary across the choice paths. Within a given program and delay combination, the predicted lifetime earnings vary across individuals according to their observed characteristics.

We use a range of variables in the vector x_i that might affect earnings, such as high school GPA, and indicators for high school track, sex, graduation cohort, and age at high school graduation. We also include a range of background characteristics, including the natural log of family income, parents' education, and an indicator for whether the student had a two-parent family. A student's parents are the individuals who are linked to their social insurance number, and need not be their birth parents. Family income is the sum of total income before taxes and after transfers for parents in the year the student graduated from high school. If only one individual is identified as a parent, only that individuals' income is included in the family income variable. Parents' education is indicated by a series of dummy variables high school or less, vocational schooling, short-, medium- and long-cycle education. For each parent, the set of dummies also includes an indicator for missing data for the parent's education.

This method of constructing counterfactual expected earnings ignores any unobserved heterogeneity in what students' believe about their future earnings prospects. We discuss the nature of any bias this might generate for our estimates in Appendix E.

Expected Student Financial Aid

Data on student financial aid, which is called "Statens Uddannelsesstøtte" (SU) in Danish, was only registered beginning in 1983. Thus, we use the students who enter university in 1983 and onward to estimate the predicted present value of student financial aid. As a measure, we take the sum of all student financial aid received in the first ten years of university and discount it by 4%. Using the full sample of student financial aid recipients, we then regress this measure on indicators for the number of years of delay and all of the same controls we used in the estimation of expected present value of earnings. Finally, we use the vector of estimates from this regression to estimate the predicted student financial aid out of sample, including for those who began university before 1983. Because we expect that there will be a considerable measurement error in this variable, we ran our model excluding student financial aid, and it has very little impact on the results.

Observed Characteristics in the Utility of Delay

We allow the utility of delay to depend on gender, high school track, age at high school graduation, graduation cohort and the local youth unemployment rate in the year of delay. To define the youth unemployment rate, we use a variable that measures individuals' employment statuses in November. We take as the denominator all individuals between the ages 17 and 21, who are not classified as outside the workforce or in education. The numerator includes all those who are fully unemployed in the last week of November. The locality is defined as the municipality (kommune in Danish) in which the student lived when he graduated from high school. We assume perfect foresight on the youth unemployment rate.

Expected Earnings in During Delay

As the earnings in a given year of delay we use the earnings from the calendar year in which the delay begins. For example, if an individual graduates from high school in 1982, the earnings in their first year of delay will come from the calendar year 1982, and earnings from their second year of delay will come from 1983. Although this does not match exactly the earnings during the academic year of delay, we choose this alignment of calendar and academic years to be consistent with indexing of the earnings after entering a program.

We use observed earnings during the first year of delay to estimate the analogous expected earnings by regressing the observed earnings in the sample that delayed by one year on all the same covariates used in the lifetime earnings. Again, we use the estimated coefficient to calculate a predicted value in and out of the estimation sample. We repeat this process for the estimated earnings during the second year of delay.

B Supplemental Information about Group II GPA Thresholds

In this appendix, we report the minimum, maximum, mean and standard deviations for the Group II GPA thresholds that are used to calibrate the beliefs about future threshold fluctuations. We used a longer time horizon, 1979-1986, to calibrate the beliefs. We also report a matrix of correlations between programs in the changes in the Group II thresholds. In the matrix of correlations, the programs with no GPA restrictions in the sample period are excluded.

Table B.1: Summary of Group II GPA Thresholds, 1979-1986

	Mean	**St. Dev.**	**Min**	**Max**
University of Copenhagen				
Medicine	8.375	0.492	7.5	8.9
Natural Sciences	6.025	0.071	6	6.2
Biology	7.363	0.873	6	8
Theology	6.262	0.374	6	6.8
Humanities	7.45	0.382	6.8	8
Law	8.1	0.37	7.4	8.6
Business/Economics	8.238	0.283	7.7	8.6
Political Science	6.75	0.578	6	7.6
Aarhus University				
Medicine	8.25	0.573	7.5	8.9
Natural Sciences	6	0	6	6
Biology	7.35	1.19	6	8.7
Theology	6	0	6	6
Humanities	7.563	0.518	6.6	8.4
Law	7.938	0.403	7.2	8.5
Social Sciences	6.2	0.566	6	7.6
Business/Economics	6	0	6	6
University of Southern Denmark				
Natural Sciences	6	0	6	6
Medicine	8.075	0.534	7.3	8.7
Humanities	6	0	6	6
Business/Economics	6.037	0.106	6	6.3
Roskilde University				
Natural Sciences	6	0	6	6
Humanities	6	0	6	6
Social Sciences	6.3	0.616	6	7.7
University of Aalborg				
Engineering	6.075	0.212	6	6.6
Humanities	6	0	6	6
Social Sciences	6	0	6	6
Danish Technical University				
Electrical Engineering	6.137	0.389	6	7.1
Engineering	6	0	6	6
Aarhus Business School				
Business/Economics	6.575	0.665	6	7.7
Copenhagen Business School				
Business/Economics	6.05	0.107	6	6.3

Notes: If supply in a program exceeded demand, the minimum GPA is set to six, which is the GPA required to complete high school.

Table B.2: Correlations Across Programs in the Annual Changes in Group II GPA Thresholds

	KU Med	KU Nat Sci	KU Bio	KU Theo	KU Hum	KU Law	KU Bus/Eco	KU PoliSci	AU MEd	AU Bio	AU Hum	AU Law	AU Soc Sci	SDU Med	SDU Bus/Eco	RU Soc Sci	AAU Eng	DTU E. Eng	ABS Bus/Eco	CBS Bus/Eco
KU Med	1																			
KU Nat Sci	0.22	1																		
KU Bio	0.21	0.54	1																	
KU Theo	0.52	-0.53	-0.35	1																
KU Hum	0.2	0.52	0.18	-0.1	1															
KU Law	0.6	0.58	0.13	-0.05	0.58	1														
KU Bus/Eco	0.25	0.48	0.78	-0.07	0	0.19	1													
KU PoliSci	0.09	0.42	-0.33	-0.23	0.61	0.41	-0.56	1												
AU MEd	0.08	-0.19	-0.18	-0.05	-0.81	-0.29	-0.18	-0.13	1											
AU Bio	-0.02	-0.71	-0.01	0.42	-0.75	-0.76	-0.03	-0.65	0.51	1										
AU Hum	0.3	0.33	-0.28	0.04	0.8	0.58	-0.47	0.91	-0.41	-0.68	1									
AU Law	0.48	0.46	-0.21	-0.11	0.36	0.88	-0.17	0.61	0.06	-0.7	0.64	1								
AU Soc Sci	-0.68	0	-0.17	-0.49	0.37	0.08	-0.21	0.16	-0.58	-0.53	0.18	0.03	1							
SDU Med	0.46	0.34	0.27	-0.07	-0.49	0.11	0.33	-0.1	0.78	0.21	-0.3	0.26	-0.75	1						
SDU Bus/Eco	-0.68	0	-0.17	-0.49	0.37	0.08	-0.21	0.16	-0.58	-0.53	0.18	0.03	1	-0.75	1					
RU Soc Sci	0.36	0.91	0.25	-0.41	0.59	0.76	0.16	0.69	-0.13	-0.81	0.62	0.75	0	0.31	0	1				
AAU Eng	-0.68	0	-0.17	-0.49	0.37	0.08	-0.21	0.16	-0.58	-0.53	0.18	0.03	1	-0.75	1	0	1			
DTU E. Eng	0	0	0.06	-0.32	-0.59	0.19	0.21	-0.38	0.57	0.05	-0.5	0.31	0	0.52	0	0	0	1		
ABS Bus/Eco	-0.02	0.74	0.13	-0.3	0.73	0.28	0.04	0.72	-0.43	-0.68	0.64	0.25	0.15	-0.11	0.15	0.73	0.15	-0.59	1	
CBS Bus/Eco	0.14	0.95	0.57	-0.6	0.56	0.43	0.33	0.52	-0.18	-0.62	0.4	0.34	0	0.27	0	0.87	0	-0.16	0.8	1

Notes: University abbreviations in the table are KU, University of Copenhagen; AU, Aarhus University; SDU, University of Southern Denmark; RU, Roskilde University; AAU, Aalbourg University; DTU, Danish Technical University; ABS, Aarhus Busines School. Field-of-study abbreviations are Med, Medical programs; Nat Sci, Natural Sciences; Bio, Biology; Theo, Theology; Hum, Humanities; Bus/Eco, Business and Ecoomics; PoliSci, Political Science; Soc Sci, Social Sciences; Eng, Engineering; E. Eng, Electrical Engineering.

C Example of a Expected Value Function

In the main body of the paper, we express the expected value function for period 2 from the period 1 point of view, conditional on Q_{i2} as,

$$\mathbb{E}_1\left[V_{i2}\left(\epsilon_{i2}, Q_{i2}, 2\right)|Q_{i2}\right] = \tau \ln\left[\sum_{p=1}^{30} q_{ip2} \exp\left(\frac{1}{\tau}\bar{U}^S_{ip2}\right)\right] + \lambda\tau$$

To evaluate the unconditional expectation, we must add across the conditional expected value functions for all possible future choice sets, weighted by the probability that they occur. For example, if a student assigns a probability of admission equal to one for 16 programs and probability equal zero for another 12 programs, this leaves 2 programs with uncertain probability of admissions, generating 4 possible choice sets. If the programs are sorted from highest to lowest thresholds, and $Prob\left[q^2_{ip} = 1\right] \equiv P^2_{ip}$ then the unconditional expected value function for this hypothetical student would be:

$$\begin{aligned}
& \mathbb{E}_1\left[V_{i2}\left(\epsilon_{i2}, Q_{i2}, 2\right)\right] \\
= \ & P^2_{i,13}P^2_{i,14}\tau \ln\left[\sum_{p=13}^{30} \exp\left(\frac{1}{\tau}\bar{U}^S_{ip2}\right)\right] \\
+ \ & \left(1 - P^2_{i,13}\right) P^2_{i,14}\tau \ln\left[\sum_{p=14}^{30} \exp\left(\frac{1}{\tau}\bar{U}^S_{ip}\right)\right] \\
+ \ & P^2_{i,13}\left(1 - P^2_{i,14}\right)\tau \ln\left[\exp\left(\frac{1}{\tau}\bar{U}^S_{i,13,2}\right) + \sum_{p=15}^{30} \exp\left(\frac{1}{\tau}\bar{U}^S_{ip2}\right)\right] \\
+ \ & \left(1 - P^2_{i,13}\right)\left(1 - P^2_{i,14}\right)\tau \ln\left[\sum_{p=15}^{30} \exp\left(\frac{1}{\tau}\bar{U}^S_{ip2}\right)\right] + \tau\lambda
\end{aligned}$$

D Further Details About Estimation and Identification

Because the solution to the model has a closed form, we use Maximum Likelihood to estimate the parameters of the model. To describe how we implement the estimation method, let $S_{ipg} = 1$ if an individual enters program p, and $D_{ig} = 1$ if an individual delays one year, after g years of delay. Both expressions equal zero otherwise. In the last period, we observe $S_{ipg} = 1$ if $d_{i0}^{0} = 1$, $d_{i1}^{0} = 1$ and $d_{i2}^{p} = 1$ maximizes the problem set out in (**??**).

Given the assumptions described in the model section, if $\tilde{Q}_{i2}$ is used to denote the set of programs for which a student is qualified, we can write the probability that $S_{ip2} = 1$ in the following way:

$$\begin{aligned} Prob\left[S_{ip2}=1\right] &= Prob\left[U_{ip2}^{S} > U_{ik2}^{S}\ \ \forall\ \ k \neq p\ \ p,k\ \in \tilde{Q}_{i2}\right] \\ &= Prob\left[\upsilon_{ip2}^{S} + \epsilon_{ip2}^{S} > \upsilon_{ik2}^{S} + \epsilon_{ik2}^{S}\ \ \forall\ \ k \neq p\ \ p,k\ \in \tilde{Q}_{i2}\right] \end{aligned} \tag{D.1}$$

Through this section, we are implicitly conditioning on all of the observed variables, including high school GPA. The set of programs for which a student is eligible is non-stochastic conditional on their GPA. Since we assume that the errors have an Extreme Value distribution, the choice probability expressed in the final line takes the familiar logit form (see **?**). Given that the probability of entering a program when not qualified is zero, the probability of observing $S_{ip2} = 1$ is:[2]

$$Prob\left[S_{ip2}=1\right] = \frac{q_{i2}^{p} * \exp\left(\upsilon_{ip2}^{S}\right)}{\sum_{j=1}^{30} q_{i2}^{j} * \exp\left(\upsilon_{ij2}^{S}\right)} \tag{D.2}$$

In the first and second periods, individuals choose between delaying and entering a program for which they are qualified. To help define the probability of delaying, define

$$\tilde{U}_{ig}^{G} = \upsilon_{ig}^{G} + \mathbb{E}_{g}\left[V_{ig+1}\left(\epsilon_{ig+1}, Q_{ig+1}, G_{ig+1}=g\right)\right] \tag{D.3}$$

Then, the probability of observing $D_{i1} = 0$ is,

$$Prob\left[D_{i1}=1\right] = Prob\left[\tilde{U}_{i1}^{G} + \epsilon_{i1}^{G} > \upsilon_{ip1}^{S} + \epsilon_{ip1}^{S}\ \ \forall p\ \in \tilde{Q}_{i1}\right] \tag{D.4}$$

Similarly, the probability of observing the first year of delay is:

$$Prob\left[D_{i0}=1\right] = Prob\left[\tilde{U}_{i0}^{G} + \epsilon_{i0}^{G} > \upsilon_{ip0}^{S} + \epsilon_{ip0}^{S}\ \ \forall p\ \in \tilde{Q}_{i0}\right] \tag{D.5}$$

Again, under the assumption that the errors are independent and follow an Extreme Value distribution we can express these probabilities in the logit form:

[2]This probability is always defined because $q_{ig}^{p} = 1$ for at least one program for all individuals.

$$Prob\left[D_{i1}=1\right] = \frac{\exp\left(\upsilon_{i1}^{G}\right)}{\exp\left(\upsilon_{10}^{G}\right)+\sum_{j=1}^{30} q_{i1}^{j} * \exp\left(\upsilon_{ij1}^{S}\right)} \tag{D.6}$$

$$Prob\left[D_{i0}=1\right] = \frac{\exp\left(\upsilon_{i0}^{G}\right)}{\exp\left(\upsilon_{0}^{G}\right)+\sum_{j=1}^{30} q_{i0}^{j} * \exp\left(\upsilon_{ij0}^{S}\right)} \tag{D.7}$$

Similarly, the probabilities of entering a program in the first and second period is:

$$Prob\left[S_{ip1}=1\right] = \frac{q_{i1}^{p} * \exp\left(\upsilon_{ip1}^{S}\right)}{\exp\left(\upsilon_{i1}^{G}\right)+\sum_{j=1}^{30} q_{i1}^{j} * \exp\left(\upsilon_{ij1}^{S}\right)} \tag{D.8}$$

$$Prob\left[S_{ip0}=1\right] = \frac{q_{i0}^{p} * \exp\left(\upsilon_{ip0}^{S}\right)}{\exp\left(\upsilon_{i0}^{G}\right)+\sum_{j=1}^{30} q_{i0}^{j} * \exp\left(\upsilon_{ij0}^{S}\right)} \tag{D.9}$$

Using these probabilities, an individual contribution to the likelihood function is:

$$\begin{aligned} L_i = & \prod_{p=1}^{30} Prob\left[S_{ip0}=1\right]^{S_{ip0}} \\ * & \prod_{p=1}^{30} Prob\left[S_{ip1}=1\right]^{S_{ip1}} * Prob\left[D_{i0}=1\right]^{G_{i0}} \\ * & \prod_{p=1}^{30} Prob\left[S_{ip2}=1\right]^{S_{ip2}} Prob\left[D_{i1}=1\right]^{D_{i1}} * Prob\left[D_{i0}=1\right]^{D_{i0}} \end{aligned} \tag{D.10}$$

We then maximize the sum of the individual log likelihoods:

$$\mathcal{L} = \sum_{i=1}^{n} \ln\left(L_i\right) \tag{D.11}$$

To maximize the function, we use the Newton-Raphson algorithm as programmed in Mata's optimize function.

In total, there are 21 parameters to estimate. There are 9 parameters in the utility of delay. In the utility of schooling, there are 7 coefficients for observed characteristics, and 4 intercepts that shift the average utility for each field of study relative to Humanities. The final parameter is the scale of the preference shocks.

The coefficients in the schooling utility equations are identified up to scale by the observed choices among individuals who are eligible to enroll in a set of programs. For example, after controlling for all other observed program characteristics, the coefficient on the "sex-match" variable is identified by the comparison between the fraction of the sample whose GPA is above the relevant threshold and who enrolls in programs in which the majority of students have the same sex and the analogous fraction enrolling in programs where their sex does not correspond with the majority. Similarly, the parameters in the delay utilities are identified by the observed delaying choices among individuals facing the same set of program choices.

The scale of the preference shocks τ will fit differences in enrollment rates that are unexplained by the average choice-specific utilities, including differences in lifetime earnings. An important identifying assumption is that the shocks are independent of the observed characteristics and each other. If any unobserved characteristics captured by the shocks are correlated with observed covariates, in particular expected future earnings, then our estimates will be biased.

The variation in GPA thresholds, in both admissions groups, provides an important source of exogenous variation. Students' contributions to the likelihood function are conditional on the set of programs for which they are eligible, meaning their GPA is above the relevant threshold. Because the GPA thresholds fluctuate based on aggregate demand and supply, individuals do not know exactly what future thresholds will be. The unpredictable fluctuations in the thresholds generates useful variation both within and across cohorts in the set of programs for which a student is eligible. Across cohorts, two students with the same GPA and the same set of characteristics, both observed and unobserved, will face a different set of program choices because of the year they graduate high school. Within a cohort, students with GPAs just above or below a threshold will face a different set of options, despite having similar grades. This variation also helps identify parameters in the value delay because the set of options to which delaying is compared depends on the GPA thresholds.

In Figures D.1 and D.2 , we report the GPA thresholds in each admissions class for the sample cohorts. In Group II, while the GPA thresholds are relevant for those delaying by one or two years, the threshold after one year would be higher because the multiplier is 1.09. A student who graduates in 1981, for example, will face the 1982 Group II thresholds after one year of delay and the 1983 thresholds after two years of delay. There is substantially more variation in the Group I thresholds, where all but two programs have changes in the GPA thresholds.

Not all of the sample is affected by every GPA fluctuation, However. Students with very high grades are eligible for all programs in every cohort. Conversely, students with low grades are unaffected by fluctuations in GPA thresholds in programs where the GPA is consistently high, such as law and medicine. Changes across cohorts in the fraction eligible for each program is another way to summarize the identifying variation in the data. We report the fraction of the sample eligible for each program in Group I by cohort in Tables D.1, D.2, and D.3.

Although we do take advantage of the exogenous variation provided by the fluctuations in GPA thresholds, this does not guarantee that our independence assumption holds. A key concern stems from unobserved heterogeneity in expected future earnings. We discuss the implications of bias arising from this sources in Appendix E.

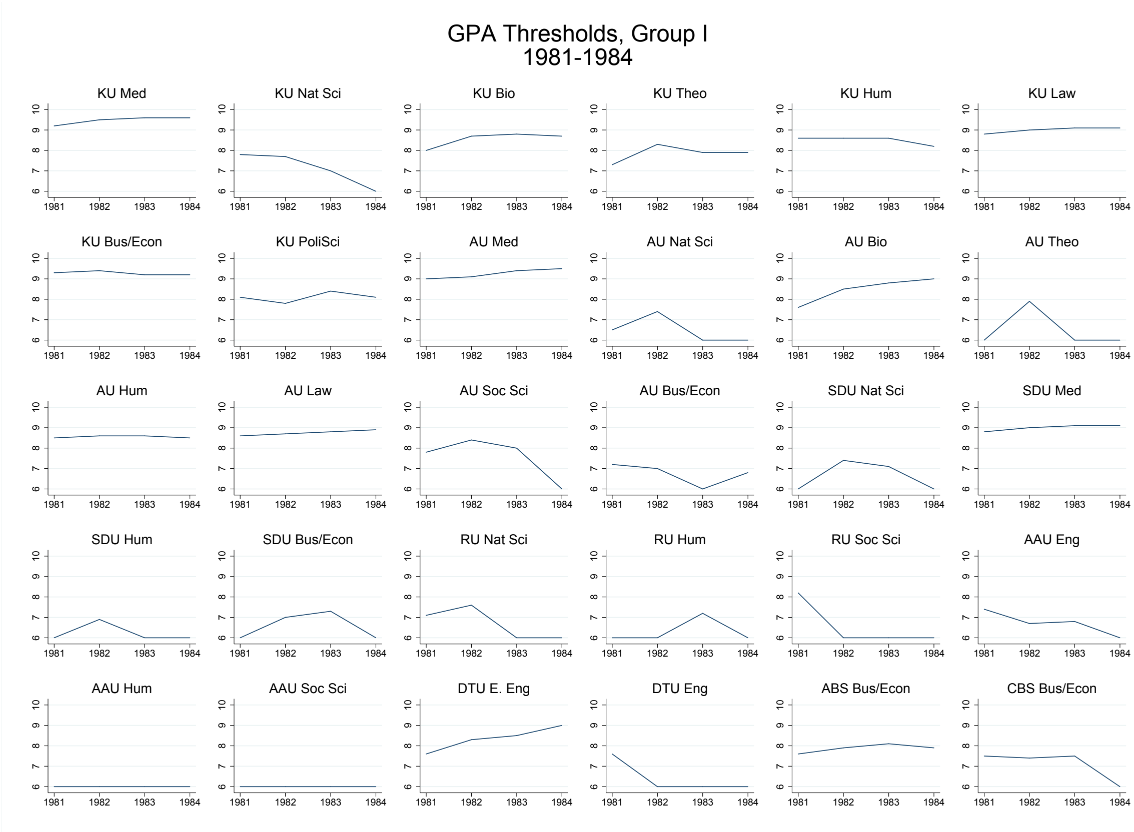

Figure D.1: GPA Thresholds in Group I Admissions Class

University abbreviations in the panel titles are KU, University of Copenhagen; AU, Aarhus University; SDU, University of Southern Denmark; RU, Roskilde University; AAU, Aalbourg University; DTU, Danish Technical University; ABS, Aarhus Busines School. Field-of-study abbreviations are Med, Medical programs; Nat Sci, Natural Sciences; Bio, Biology; Theo, Theology; Hum, Humanities; Bus/Econ, Business and Economics; PoliSci, Political Science; Soc Sci, Social Sciences; Eng, Engineering; E. Eng, Electrical Engineering.

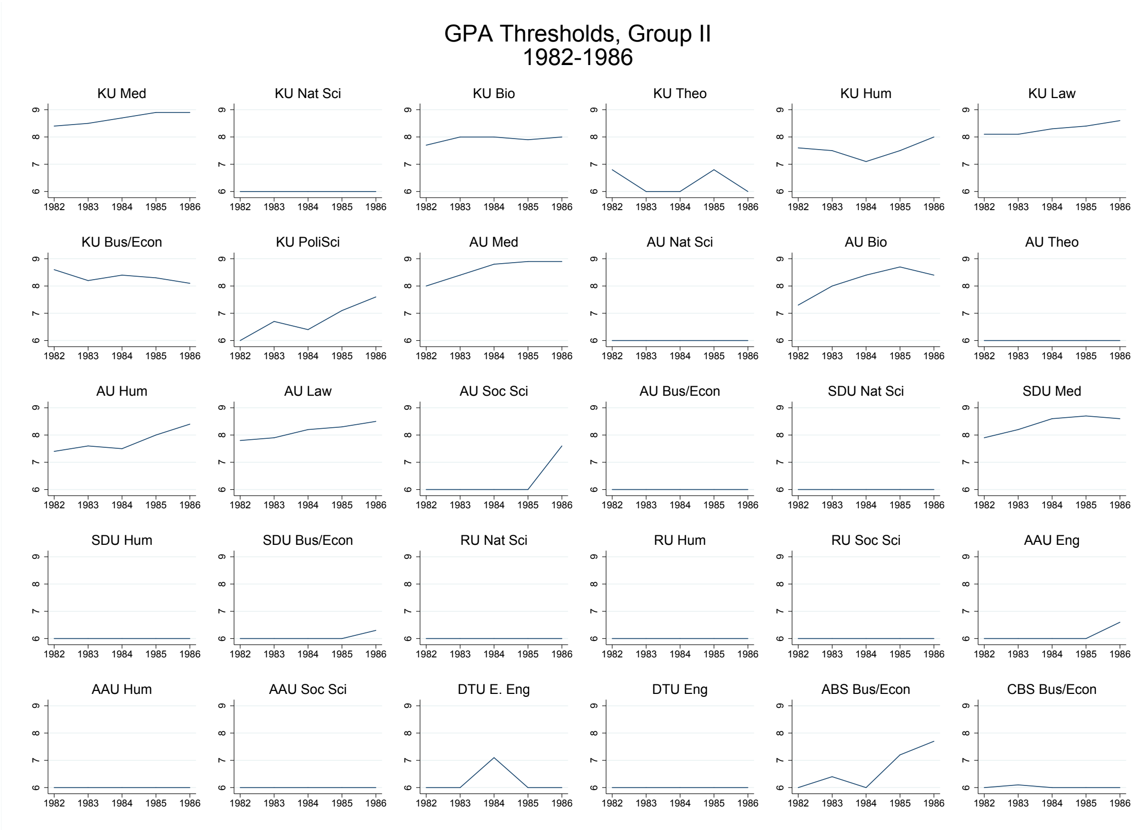

Figure D.2: GPA Thresholds in Group II Admissions Class

University abbreviations in the panel titles are KU, University of Copenhagen; AU, Aarhus University; SDU, University of Southern Denmark; RU, Roskilde University; AAU, Aalbourg University; DTU, Danish Technical University; ABS, Aarhus Busines School. Field-of-study abbreviations are Med, Medical programs; Nat Sci, Natural Sciences; Bio, Biology; Theo, Theology; Hum, Humanities; Bus/Econ, Business and Economics; PoliSci, Political Science; Soc Sci, Social Sciences; Eng, Engineering; E. Eng, Electrical Engineering.

Table D.1: Fraction of the Sample With a GPA Above the Threshold After No Delay, By Cohort

	1981	**1982**	**1983**	**1984**
University of Copenhagen				
Medicine	0.313	0.202	0.213	0.227
Natural Sciences	0.833	0.850	0.972	1.000
Biology	0.804	0.548	0.469	0.558
Theology	0.939	0.671	0.813	0.835
Humanities	0.576	0.589	0.583	0.746
Law	0.439	0.394	0.395	0.420
Business/Economics	0.237	0.275	0.360	0.378
Political Science	0.768	0.827	0.657	0.776
Aarhus University				
Medicine	0.355	0.394	0.282	0.227
Natural Sciences	0.997	0.934	1.000	1.000
Biology	0.905	0.589	0.469	0.420
Theology	1.000	0.827	1.000	1.000
Humanities	0.576	0.589	0.583	0.595
Law	0.576	0.548	0.469	0.484
Social Sciences	0.833	0.671	0.787	1.000
Business/Economics	0.951	0.975	1.000	0.978
University of Southern Denmark				
Natural Sciences	1.000	0.934	0.961	1.000
Medicine	0.439	0.394	0.395	0.420
Humanities	1.000	0.982	1.000	1.000
Business/Economics	1.000	0.975	0.923	1.000
Roskilde University				
Natural Sciences	0.972	0.897	1.000	1.000
Humanities	1.000	1.000	0.936	1.000
Social Sciences	0.735	1.000	1.000	1.000
University of Aalborg				
Engineering	0.939	0.986	0.977	1.000
Humanities	1.000	1.000	1.000	1.000
Social Sciences	1.000	1.000	1.000	1.000
Danish Technical University				
Electrical Engineering	0.905	0.671	0.583	0.420
Engineering	0.905	1.000	1.000	1.000
Aarhus Business School				
Business/Economics	0.905	0.827	0.759	0.835
Copenhagen Business School				
Business/Economics	0.924	0.934	0.907	1.000

Table D.2: Fraction of the Sample With a GPA Above the Threshold After One Year of Delay, By Cohort

	1981	**1982**	**1983**	**1984**
University of Copenhagen				
Medicine	0.355	0.311	0.246	0.197
Natural Sciences	1.000	1.000	1.000	1.000
Biology	0.656	0.548	0.545	0.595
Theology	0.939	1.000	1.000	0.926
Humanities	0.698	0.741	0.865	0.746
Law	0.485	0.509	0.431	0.420
Business/Economics	0.237	0.466	0.395	0.451
Political Science	1.000	0.947	0.972	0.879
Aarhus University				
Medicine	0.534	0.394	0.213	0.197
Natural Sciences	1.000	1.000	1.000	1.000
Biology	0.804	0.548	0.395	0.261
Theology	1.000	1.000	1.000	1.000
Humanities	0.768	0.708	0.727	0.558
Law	0.616	0.589	0.469	0.451
Social Sciences	1.000	1.000	1.000	1.000
Business/Economics	1.000	1.000	1.000	1.000
University of Southern Denmark				
Natural Sciences	1.000	1.000	1.000	1.000
Medicine	0.576	0.466	0.282	0.261
Humanities	1.000	1.000	1.000	1.000
Business/Economics	1.000	1.000	1.000	1.000
Roskilde University				
Natural Sciences	1.000	1.000	1.000	1.000
Humanities	1.000	1.000	1.000	1.000
Social Sciences	1.000	1.000	1.000	1.000
University of Aalborg				
Engineering	1.000	1.000	1.000	1.000
Humanities	1.000	1.000	1.000	1.000
Social Sciences	1.000	1.000	1.000	1.000
Danish Technical University				
Electrical Engineering	1.000	1.000	0.865	1.000
Engineering	1.000	1.000	1.000	1.000
Aarhus Business School				
Business/Economics	1.000	0.975	1.000	0.861
Copenhagen Business School				
Business/Economics	1.000	0.990	1.000	1.000

Table D.3: Fraction of the Sample With a GPA Above the Threshold After Two Years of Delay, By Cohort

	1981	**1982**	**1983**	**1984**
University of Copenhagen				
Medicine	0.576	0.548	0.469	0.484
Natural Sciences	1.000	1.000	1.000	1.000
Biology	0.804	0.798	0.813	0.804
Theology	1.000	1.000	0.977	1.000
Humanities	0.924	0.967	0.907	0.804
Law	0.735	0.671	0.657	0.558
Business/Economics	0.735	0.671	0.657	0.746
Political Science	0.993	0.998	0.961	0.898
Aarhus University				
Medicine	0.656	0.466	0.469	0.484
Natural Sciences	1.000	1.000	1.000	1.000
Biology	0.804	0.671	0.545	0.681
Theology	1.000	1.000	1.000	1.000
Humanities	0.905	0.918	0.787	0.681
Law	0.833	0.741	0.657	0.595
Social Sciences	1.000	1.000	1.000	0.898
Business/Economics	1.000	1.000	1.000	1.000
University of Southern Denmark				
Natural Sciences	1.000	1.000	1.000	1.000
Medicine	0.735	0.548	0.545	0.558
Humanities	1.000	1.000	1.000	1.000
Business/Economics	1.000	1.000	1.000	0.997
Roskilde University				
Natural Sciences	1.000	1.000	1.000	1.000
Humanities	1.000	1.000	1.000	1.000
Social Sciences	1.000	1.000	1.000	1.000
University of Aalborg				
Engineering	1.000	1.000	1.000	0.992
Humanities	1.000	1.000	1.000	1.000
Social Sciences	1.000	1.000	1.000	1.000
Danish Technical University				
Electrical Engineering	1.000	0.967	1.000	1.000
Engineering	1.000	1.000	1.000	1.000
Aarhus Business School				
Business/Economics	0.998	1.000	0.949	0.879
Copenhagen Business School				
Business/Economics	1.000	1.000	1.000	1.000

E Unobserved Skills

We estimate the expected income associated with each different schooling and delay choice using group averages, after controlling for a wide range of observed characteristics, including sex, high school track, and GPA. These characteristics explain much of the observed variation in earnings, however, if students predict their future earnings based on unobserved characteristics our estimation cannot take this into account. In this appendix, we focus on how ignoring unobserved program-specific skills in the estimation can cause bias in the amount of switching between programs in the baseline and free-entry experiment which we will refer to as the counterfactual. To help us describe the nature of any possible bias, we contrast the set of observed choices in the baseline and counterfactual in the estimated model, to what we would expect to see in a true model with unobserved skills. The differences between the estimates and the truth will depend on the strength and the sign of the correlation between unobserved program-specific skills and the variance of those skills.

We begin with the case where the unobserved skills are positively correlated between the programs chosen in the baseline and counterfactual. In this case, when the constraint of the high-demand program is lifted, the higher skilled students from the low-demand programs will enter the high-demand programs. In the high-demand program, the new students may either be of lower or higher unobserved skills. If the students are of relatively low unobserved skills relative to the predicted group average of their new program, our model will over estimate the probability of switching program because we assign a higher premium to switching compared to a model with selection on unobserved skills. If the students are of high unobserved skills relative to the predicted group average of their new program, we cannot assign the bias between our model and a model with unobserved skills. That bias will depend on the strength of the correlation in program-specific skills and the variance of the unobserved skills in the different programs. Knowing this, would tell us how large the unobserved skills are in the baseline and new program compared to the predicted group averages.

If skills in students' baseline and new program are negatively correlated then when the constraint of the high demand program is lifted, the lower skilled students from the low demand programs will enter the high demand programs. In the high demand program, again, the new students may be of lower or higher unobserved skills.

If the students are of low unobserved skills relative to the predicted group average in their new program, we cannot assign the bias between our model and a model with unobserved heterogeneity. The bias will depend on the strength of the correlation in program-specific skills and the variance of the unobserved skills in the different programs. If the students are of high unobserved skills relative to the predicted group average of their new program, our model will under estimate the probability of switching program because we assign the a lower premium to switching compared to a model with selection on unobserved skills.

For the constrained students, we believe most of them will have some form of positive correlation between the skills in their baseline program and new program. We base this on admissions application data from more recent cohorts, where it is observed that students usually rank programs from the same field of study or same level of math. An example where skills may be negatively correlated is humanities and medicine, but we would expect that very few students rank both medicine and humanities in their application. More students rank medicine and natural science in their application but here, we believe, there is a positive correlation in unobserved skills. Since we believe that the most prevalent correlation between skills in the programs is positive, then the bias is either indeterminant or positive where our results would be an upper bound on the amount of switching in the counterfactual.

F Estimated Model Parameters

Table F.1: Model Estimation Results (Standard Errors in Parentheses)

Value of Schooling			
Father holds Candidature in same field of study	12.747 (1.372)	Program located in own city	10.093 (1.092)
Mother holds Candidature in same field of study	6.467 (1.741)	Program located in own region	27.524 (2.388)
Gender match with field of study	23.217 (2.053)	HS track match with field of study	11.178 (1.053)
Student-Teacher Ratio	1.193 (0.128)		
Field of study intercepts, relative to Humanities			
Natural sciences	-2.048 (0.750)	Social sciences	0.239 (0.715)
Engineering	10.181 (1.282)	Medical programs	12.837 (1.437)
Value of Delaying			
Local youth unemployment rate	9.736 (4.435)	Age	-0.831 (0.078)
Female, first year	5.655 (0.799)	Female, second year	0.345 (0.812)
Math track, first year	-11.050 (1.102)	Math track, second year	-7.875 (0.975)
Cohort intercepts, relative to 1984			
1981	-1.265 (0.617)	1982	-1.887 (0.609)
1983	-2.240 (0.614)		
Preference shocks			
$\exp(\tau)$	2.897 (0.086)		

Notes: A student's gender matches with their field of study if the majority in the field are of the same gender. Medicine and Humanities are coded as female, and Natural Sciences, Social Sciences, and Engineering are coded as male. The analogous is true for "gender match with high school (HS) track". Medicine, Natural Sciences, and Engineering are coded as math track fields, while Humanities and Social Sciences are coded as language track fields.

G Model Fit

To further assess the fit of the model, we show how well our model can predict the aggregate distributions of delay and field of study. Tables G.1 and G.2 show these distributions, in and out of sample, for years of delay and field of study respectively. For a visual representation, we also present the same distributions in Figures G.1 and G.2.

The top panel in G.2 shows the overall distribution of field of study, and reveals that, in the sample, the model matches the field-of-study distributions well. The simulated prediction from the model within the sample years 1981-1984 matches the distribution of field of study in the data. With the out-of-sample prediction, we are interested to see how well the model fits the data from the 1980 cohort, which was not used in the estimation. The model matches the direction in the out-of-sample prediction for all fields, except Humanities, such that when the fraction in the field of study increases (decreases) between 1980 and 1981-1984 in the data, so does the predictions from the simulated 1980 cohort. The four sub-figures in the bottom panel of G.2 show that the sample predictions most closely follow the data among men and high school math-track students.

Figure G.1 shows the distribution of delay in and out of sample. Here, the model again matches the data in the sample very well. However, the out-of-sample fit is less precise. To figure out why the model has a difficult time matching the data for the 1980 distribution of delay, we refer back to Figure **??** in the main text. In Figure **??**, we see that some large programs in Humanities and Social Science, such as KU PoliSci, AAU Soc Sci, RU Soc Sci, RU Hum, and SDU Hum, have increases in the fraction of students entering without delay between 1980 and 1981-1984 that we cannot match with the model because these programs have no concurrent fluctuations in their GPA threshold. Such changes in the propensity to delay are not captured well by the model. However, the magnitude of our under-prediction is not sufficiently large to substantially change the main conclusions drawn from our findings.

Table G.1: Model Fit: Distribution of Delay (Standard Errors in Parentheses)

	In Sample, 1981-84		Out of Sample, 1980	
	Simulated	**Data**	**Simulated**	**Data**
Total				
0 years delay	0.547	0.546	0.563	0.519
	(0.004)	(0.004)	(0.006)	(0.008)
1 year delay	0.294	0.295	0.276	0.313
	(0.003)	(0.003)	(0.003)	(0.008)
2 years delay	0.160	0.158	0.160	0.167
	(0.003)	(0.003)	(0.005)	(0.006)
Males				
0 years delay	0.595	0.595	0.614	0.560
	(0.005)	(0.005)	(0.006)	(0.010)
1 year delay	0.271	0.272	0.253	0.293
	(0.003)	(0.004)	(0.003)	(0.009)
2 years delay	0.134	0.133	0.133	0.147
	(0.003)	(0.003)	(0.005)	(0.007)
Females				
0 years delay	0.461	0.460	0.469	0.443
	(0.006)	(0.006)	(0.009)	(0.014)
1 year delay	0.334	0.337	0.321	0.352
	(0.006)	(0.006)	(0.006)	(0.014)
2 years delay	0.205	0.204	0.211	0.204
	(0.005)	(0.005)	(0.007)	(0.011)
Math Track				
0 years delay	0.586	0.585	0.612	0.572
	(0.005)	(0.004)	(0.007)	(0.010)
1 year delay	0.277	0.279	0.258	0.290
	(0.004)	(0.004)	(0.004)	(0.009)
2 years delay	0.137	0.136	0.130	0.138
	(0.004)	(0.003)	(0.005)	(0.007)
Language Track				
0 years delay	0.424	0.425	0.431	0.378
	(0.007)	(0.008)	(0.010)	(0.016)
1 year delay	0.346	0.346	0.327	0.376
	(0.004)	(0.007)	(0.005)	(0.016)
2 years delay	0.230	0.229	0.242	0.246
	(0.006)	(0.007)	(0.009)	(0.014)

Table G.2: Model Fit: Distribution of Field of Study (Standard Errors in Parentheses)

	In Sample, 1981-84		**Out of Sample, 1980**	
	Simulated	**Data**	**Simulated**	**Data**
Total				
Humantities	0.147	0.147	0.143	0.174
	(0.002)	(0.003)	(0.002)	(0.006)
Natural Science	0.186	0.188	0.194	0.192
	(0.003)	(0.003)	(0.003)	(0.007)
Social Science	0.366	0.367	0.350	0.321
	(0.004)	(0.004)	(0.004)	(0.008)
Engineering	0.230	0.225	0.210	0.196
	(0.003)	(0.003)	(0.003)	(0.007)
Medical programs	0.071	0.073	0.103	0.117
	(0.002)	(0.002)	(0.002)	(0.005)
Males				
Humantities	0.078	0.081	0.077	0.108
	(0.002)	(0.003)	(0.002)	(0.006)
Natural Science	0.223	0.196	0.236	0.202
	(0.004)	(0.004)	(0.004)	(0.008)
Social Science	0.370	0.369	0.352	0.332
	(0.005)	(0.005)	(0.004)	(0.010)
Engineering	0.276	0.306	0.252	0.270
	(0.004)	(0.004)	(0.004)	(0.009)
Medical programs	0.052	0.049	0.083	0.088
	(0.001)	(0.002)	(0.002)	(0.006)
Females				
Humantities	0.270	0.262	0.266	0.296
	(0.005)	(0.006)	(0.005)	(0.013)
Natural Science	0.119	0.174	0.115	0.174
	(0.002)	(0.005)	(0.003)	(0.011)
Social Science	0.360	0.364	0.346	0.302
	(0.004)	(0.006)	(0.005)	(0.013)
Engineering	0.148	0.084	0.132	0.058
	(0.002)	(0.004)	(0.003)	(0.007)
Medical programs	0.103	0.116	0.141	0.171
	(0.002)	(0.004)	(0.003)	(0.011)
Math Track				
Humantities	0.097	0.060	0.086	0.071
	(0.002)	(0.002)	(0.002)	(0.005)
Natural Science	0.234	0.234	0.250	0.247
	(0.004)	(0.004)	(0.004)	(0.008)
Social Science	0.297	0.333	0.269	0.291
	(0.005)	(0.004)	(0.004)	(0.009)
Engineering	0.289	0.295	0.271	0.268
	(0.004)	(0.004)	(0.004)	(0.009)
Medical programs	0.083	0.078	0.124	0.124
	(0.002)	(0.002)	(0.003)	(0.006)
Language Track				
Humantities	0.308	0.420	0.296	0.452
	(0.005)	(0.008)	(0.005)	(0.016)
Natural Science	0.034	0.041	0.039	0.044
	(0.002)	(0.003)	(0.002)	(0.007)
Social Science	0.585	0.474	0.571	0.404
	(0.005)	(0.008)	(0.005)	(0.016)
Engineering	0.043	0.006	0.046	0.003
	(0.002)	(0.001)	(0.002)	(0.002)
Medical programs	0.030	0.059	0.048	0.098
	(0.001)	(0.004)	(0.002)	(0.010)

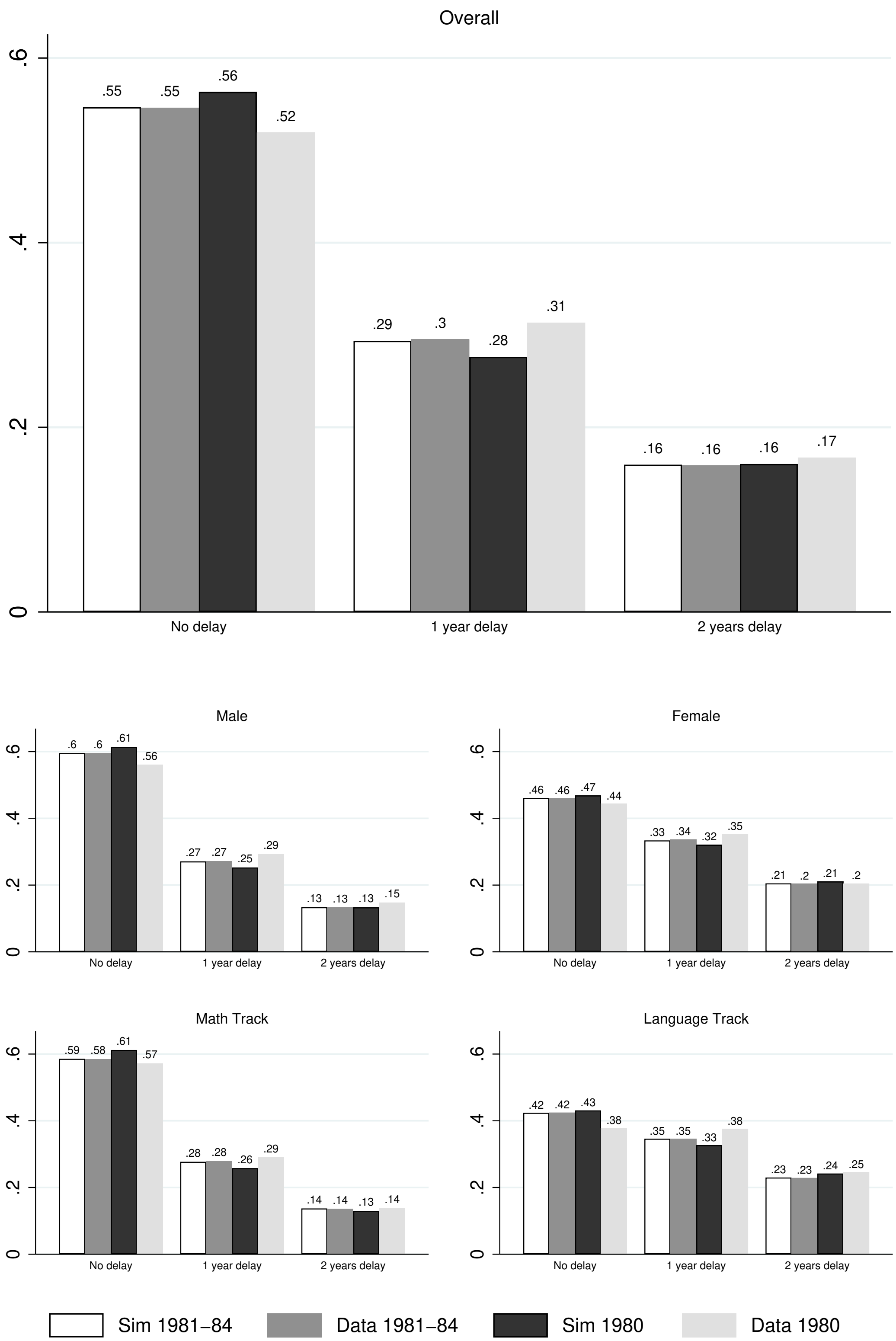

Figure G.1: Model Fit: Distribution of Delay

Notes: Model estimated using data from 1981-1984. Data used to assess fit from 1980.

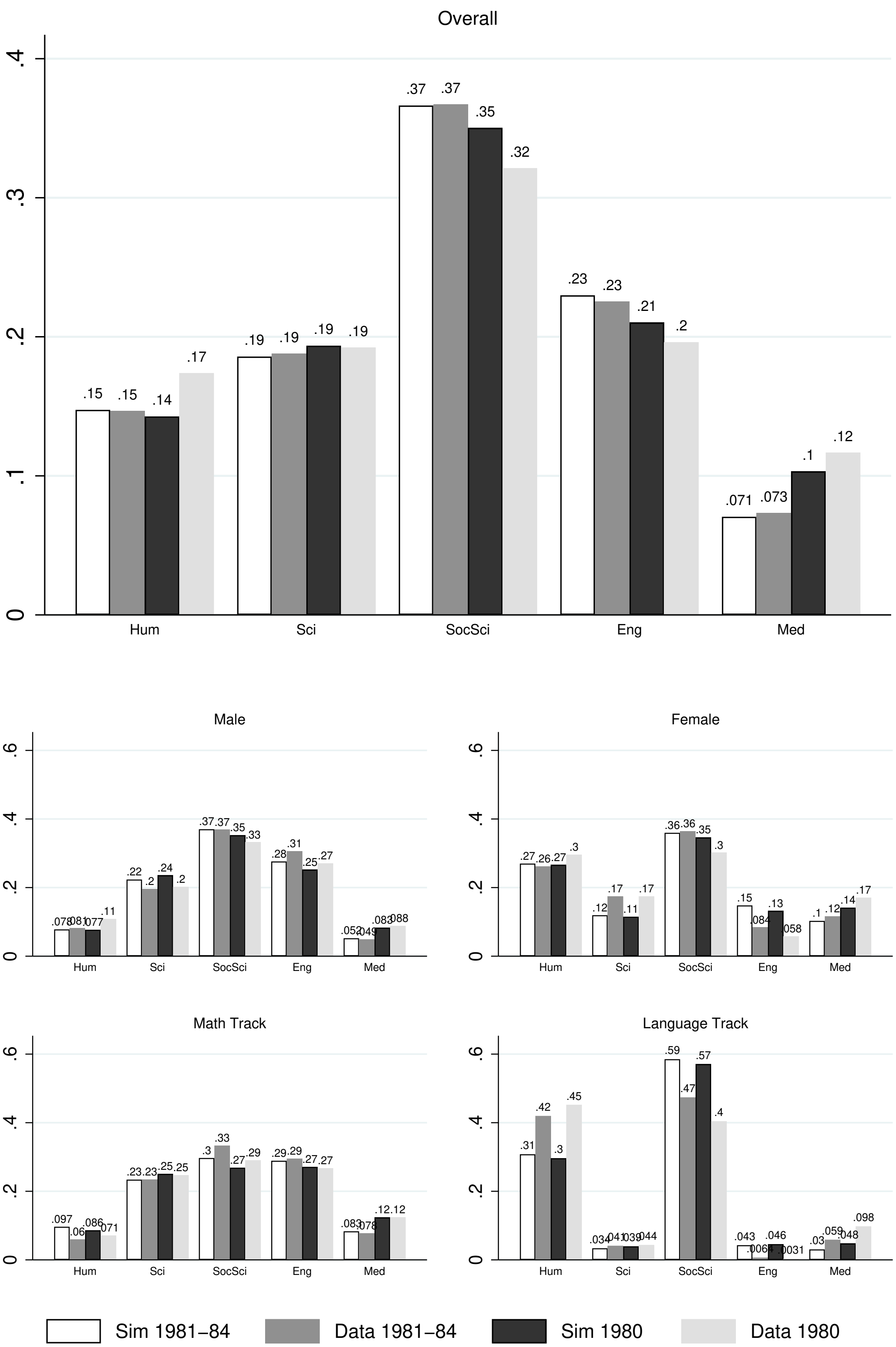

Figure G.2: Field of Study Fit: Distribution of Delay

Notes: Model estimated using data from 1981-1984. Data used to assess fit from 1980. Abbreviations in the labels are Hum, Humanities; Sci, Natural Science; SocSci, Social Science; Eng, Engineering; Med, Medical Programs.

H Gross Flows from Baseline to the Free-entry-except-Medicine

Table H.1: Gross flows in the joint distribution of delay and field of study from baseline to free-entry-except-medicine

Baseline															
	Free Entry Except Medicine														
Zero years delay															
Hum.	0.0646	0.0011	0.0047	0.0010	0.0000	0.0001	0.0000	0.0002	0.0000	0.0000	0.0000	0.0000	0.0001	0.0000	0.0000
Sci.	0.0011	0.0996	0.0084	0.0027	0.0000	0.0000	0.0001	0.0002	0.0001	0.0000	0.0000	0.0000	0.0001	0.0000	0.0000
Soc. Sci.	0.0019	0.0035	0.1816	0.0028	0.0000	0.0001	0.0001	0.0004	0.0001	0.0000	0.0001	0.0001	0.0002	0.0000	0.0000
Eng.	0.0013	0.0036	0.0105	0.1135	0.0000	0.0000	0.0001	0.0002	0.0001	0.0000	0.0000	0.0000	0.0001	0.0001	0.0000
Med.	0.0000	0.0000	0.0002	0.0000	0.0418	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
One year delay															
Hum.	0.0014	0.0011	0.0048	0.0010	0.0000	0.0366	0.0005	0.0020	0.0000	0.0000	0.0000	0.0000	0.0001	0.0000	0.0000
Sci.	0.0012	0.0028	0.0061	0.0025	0.0000	0.0002	0.0348	0.0018	0.0001	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Soc. Sci.	0.0027	0.0039	0.0131	0.0035	0.0000	0.0007	0.0015	0.0861	0.0002	0.0000	0.0001	0.0001	0.0002	0.0000	0.0000
Eng.	0.0017	0.0040	0.0092	0.0047	0.0000	0.0004	0.0013	0.0029	0.0441	0.0000	0.0000	0.0000	0.0001	0.0000	0.0000
Med.	0.0000	0.0000	0.0001	0.0000	0.0000	0.0000	0.0000	0.0001	0.0000	0.0158	0.0000	0.0000	0.0000	0.0000	0.0000
Two years delay															
Hum.	0.0011	0.0008	0.0035	0.0008	0.0000	0.0003	0.0003	0.0013	0.0001	0.0000	0.0188	0.0002	0.0008	0.0000	0.0000
Sci.	0.0007	0.0016	0.0033	0.0013	0.0000	0.0002	0.0006	0.0011	0.0001	0.0000	0.0001	0.0143	0.0006	0.0000	0.0000
Soc. Sci.	0.0018	0.0022	0.0083	0.0020	0.0000	0.0005	0.0009	0.0031	0.0001	0.0000	0.0003	0.0005	0.0436	0.0000	0.0000
Eng.	0.0009	0.0021	0.0048	0.0024	0.0000	0.0002	0.0008	0.0015	0.0002	0.0000	0.0001	0.0005	0.0009	0.0175	0.0000
Med.	0.0000	0.0000	0.0003	0.0000	0.0000	0.0000	0.0001	0.0002	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0119

Notes: The joint distribution of delay and field of study in the baseline and "Free Entry Except Medicine" counterfactuals is reported. The baseline specification uses the model admissions constraints. "Free Entry Except Med." means there are no restrictions in any period in every other program except Medical programs, for which the model restrictions apply in every year.

I Alternative Assumptions for Beliefs about Future GPA Thresholds

In the main model, we truncate the distributions on Group II GPA threshold beliefs using one standard deviation to limit the number of programs into which students are uncertain they will be admitted in the future. With one standard deviation the maximum number of programs over which any student is uncertain is ten, which requires computing a weighted sum of 210 possible future choice sets.

In this appendix, we report results from a model where we assume students believe future thresholds are uniformly distributed, but instead we use the full support over the years 1979 to 1986.[3] This appendix also includes models where the students believe the distributions are truncated normal and "uniform with drift". The truncation point in the truncated normal beliefs are one standard deviation above and below the mean. We describe how we calibrate the "uniform with drift" beliefs below in I.

Our key findings are robust to different assumptions about these beliefs. In Section I, I, I we show the parameter estimates and the counterfactual results from the models with beliefs that are modelled as truncated normal, full support, and uniform with drift. Table I.1 summarises changes from the baseline to the counterfactual results for the fraction of students entering university with no delay under these three models and the main model. From Table I.1 we see that all models have an 8.6 to 9.6 percentage point increase in students entering without delay when going from the Baseline to the Free Entry counterfactual. When comparing the baseline to the free entry with no delay experiment, all the models again produce results in the same direction, with a larger increase in the fraction of students going directly to university than under the Free-Entry counterfactual. For the final counterfactual, Free entry except Medicine, we see similar magnitudes in student entering university without delay as in the Free Entry counterfactual for all ways of modelling beliefs, except for the "Uniform with Drift". When we model the beliefs with a drift, the fraction of students entering university without delay is the highest, most likely because Medicine is one of the programs with high GPA's and positive drift.

[3] The minimums and maximums, as well as the means and standard deviations are reported in Supplemental Appendix B.

Table I.1: Percentage Point Changes in the Fraction Entering University With No Delay, Comparing the Baseline to Three Counterfactuals

	Free Entry	Free Entry no Delay	Free Entry except Medicine
Main Specification	0.0932	0.1104	0.0988
Truncated Normal	0.0935	0.1104	0.099
Maximum Variance	0.0864	0.1106	0.0873
Uniform with Drift	0.0958	0.1058	0.1321

Notes: The numbers in the table show how the fraction of students entering university without delay changes when comparing the baseline to different counterfactual admissions restrictions. The rows of the table represent different models estimated under alternative assumptions about students' beliefs about future GPA thresholds. The main specification assumes that students believe GPAs follow a uniform distribution with a support that is bounded by one standard deviation above and below the mean. In the "Truncated Normal" model, students believe the distribution is normal but truncated at one standard deviation above and below the mean. "Maximum Variance" means students believe the distribution is uniform, with a lower and upper bound corresponding to the minimum and maximum GPA threshold observed in the period between 1979 and 1986. Finally, "Uniform with Drift" means students believe the thresholds are uniformly distributed but the mean follows a non-stochastic trend.
The baseline admissions counterfactual uses the model admissions constraints. "Free Entry" means there are no restrictions on any program in any period. Under the "Free Entry with no Delay" counterfactual there are no restrictions if students enter university directly from university, but if they delay they face the usual model restrictions after one or two years of delay. "Free Entry Except Med." means there are no restrictions in any period in every other program except Medical programs, for which the model restrictions apply in every year.

Truncated Normal Beliefs

Table I.2: Counterfactual Admissions Constraints: Distribution of Delay-Using Beliefs about GPA Thresholds that Follow a Truncated Normal Distribution (Standard Errors in Parentheses)

	Baseline	**Free Entry**	**Free Entry with no delay**	**Free Entry Except Med.**
0 years delay	0.5465	0.6400	0.6569	0.6455
1 year delay	0.2937	0.2545	0.2238	0.2423
2 years delay	0.1598	0.1054	0.1193	0.1122

Notes: Based on the model estimated under the assumption that students believe future GPA thresholds follow a normal distribution that is truncated at one standard deviation above and below the mean.
Distributions of delays are simulated under different counterfactual admissions constraints. The baseline specification uses the model admissions constraints. "Free Entry" means there are no restrictions on any program in any period. Under the "Free Entry with no Delay" counterfactual there are no restrictions if students enter university directly from university, but if they delay they face the usual model restrictions after one or two years of delay. "Free Entry Except Med." means there are no restrictions in any period in every other program except Medical programs, for which the model restrictions apply in every year.

Table I.3: Gross flows in the distribution of delay from the baseline to the free entry experiment-Using Beliefs about GPA Thresholds that Follow a Truncated Normal Distribution

	Free Entry		
	Zero years	One year	Two years
Baseline			
Zero years	0.5369	0.0069	0.0027
One year	0.0653	0.2260	0.0024
Two years	0.0379	0.0216	0.1003

Notes: Based on the model estimated under the assumption that students believe future GPA thresholds follow a normal distribution that is truncated at one standard deviation above and below the mean. The joint distribution of delay in the baseline and "Free Entry" counterfactuals is reported.
The baseline specification uses the model admissions constraints. "Free Entry" means there are no restrictions on any program in any period.

Table I.4: Gross flows in the distribution of delay from free entry to the free entry without delay experiment-Using Beliefs about GPA Thresholds that Follow a Truncated Normal Distribution

	Free Entry Without Delay		
	Zero years	One year	Two years
Free Entry			
Zero years	0.6400	0.0000	0.0000
One year	0.0122	0.2215	0.0208
Two years	0.0047	0.0023	0.0985

Notes: Based on the model estimated under the assumption that students believe future GPA thresholds follow a normal distribution that is truncated at one standard deviation above and below the mean.
The joint distribution of delay in the "Free Entry" and "Free Entry Without Delay" counterfactuals is reported. "Free Entry" means there are no restrictions on any program in any period. Under the "Free Entry with no Delay" counterfactual there are no restrictions if students enter university directly from university, but if they delay they face the usual model restrictions after one or two years of delay.

Table I.5: Counterfactual Admissions Constraints: Distribution of Field of Study-Using Beliefs about GPA Thresholds that Follow a Truncated Normal Distribution (Standard Errors in Parentheses)

	Baseline	**Free Entry**	**Free Entry Except Med.**
Humantities	0.1481	0.1204	0.1395
Natural Science	0.1852	0.1499	0.1827
Social Science	0.3661	0.3530	0.4066
Engineering	0.2301	0.1685	0.2016
Medical programs	0.0706	0.2083	0.0697

Notes: Based on the model estimated under the assumption that students believe future GPA thresholds follow a normal distribution that is truncated at one standard deviation above and below the mean.
Distributions of field of study are simulated under different counterfactual admissions constraints. The baseline specification uses the model admissions constraints. "Free Entry" means there are no restrictions on any program in any period. "Free Entry Except Med." means there are no restrictions in any period in every other program except Medical programs, for which the model restrictions apply in every year.

Table I.6: Model Estimation Results-Using Beliefs about GPA Thresholds that Follow a Truncated Normal Distribution (Standard Errors in Parentheses)

Value of Schooling			
Father holds Candidature in same field of study	12.752	Program located in own city	10.095
	(1.373)		(1.092)
Mother holds Candidature in same field of study	6.466	Program located in own region	27.532
	(1.742)		(2.390)
Gender match with field of study	23.225	HS track match with field of study	11.185
	(2.056)		(1.054)
Student-teacher Ratio	1.193		
	(0.128)		
Field of study intercepts, relative to Humanities			
Natural sciences	-2.050	Social sciences	0.240
	(0.750)		(0.715)
Engineering	10.184	Medical programs	12.845
	(1.283)		(1.438)
Value of Delaying			
Local youth unemployment rate	9.729	Age	-0.832
	(4.437)		(0.078)
Female, first year	5.658	Female, second year	0.341
	(0.800)		(0.813)
Math track, first year	-11.057	Math track, second year	-7.884
	(1.104)		(0.976)
Cohort intercepts, relative to 1984			
1981	-1.264	1982	-1.887
	(0.617)		(0.609)
1983	-2.241		
	(0.614)		
Preference shocks			
$\exp(\tau)$	2.897		
	(0.086)		

Notes: Estimates from the model that assumes students believe future GPA thresholds follow a normal distribution that is truncated at one standard deviation above and below the mean.
A student's gender matches with their field of study if the majority in the field are of the same gender. Medicine and Humanities are coded as female, and Natural Sciences, Social Sciences, and Engineering are coded as male. The analogous is true for "gender match with high school (HS) track". Medicine, Natural Sciences, and Engineering are coded as math track fields, while Humanities and Social Sciences are coded as language track fields.

Uniform Beliefs with Maximum Variance

Table I.7: Counterfactual Admissions Constraints: Distribution of Delay-Using Beliefs about GPA Thresholds that Follow a Uniform Distribution with Maximum Variance (Standard Errors in Parentheses)

	Baseline	**Free Entry**	**Free Entry with no delay**	**Free Entry Except Med.**
0 years delay	0.5469	0.6333	0.6575	0.6342
1 year delay	0.2938	0.2578	0.2234	0.2481
2 years delay	0.1594	0.1090	0.1191	0.1177

Notes: Based on the model estimated under the assumption that students believe future GPA thresholds follow a uniform distribution with a lower and upper bound corresponding to the minimum and maximum GPA threshold observed in the period between 1979 and 1986.
Distributions of delays are simulated under different counterfactual admissions constraints. The baseline specification uses the model admissions constraints. “Free Entry” means there are no restrictions on any program in any period. Under the “Free Entry with no Delay” counterfactual there are no restrictions if students enter university directly from university, but if they delay they face the usual model restrictions after one or two years of delay. “Free Entry Except Med.” means there are no restrictions in any period in every other program except Medical programs, for which the model restrictions apply in every year.

Table I.8: Gross flows in the distribution of delay from the baseline to the free entry experiment-Using Beliefs about GPA Thresholds that Follow a Uniform Distribution with Maximum Variance

	Free Entry		
	Zero years	One year	Two years
Baseline			
Zero years	0.5337	0.0094	0.0038
One year	0.0634	0.2271	0.0032
Two years	0.0362	0.0212	0.1020

Notes: Based on the model estimated under the assumption that students believe future GPA thresholds follow a uniform distribution with a lower and upper bound corresponding to the minimum and maximum GPA threshold observed in the period between 1979 and 1986.
The joint distribution of delay in the baseline and “Free Entry” counterfactuals is reported. The baseline specification uses the model admissions constraints. “Free Entry” means there are no restrictions on any program in any period.

Table I.9: Gross flows in the distribution of delay from free entry to the free entry without delay experiment-Using Beliefs about GPA Thresholds that Follow a Uniform Distribution with Maximum Variance

	Free Entry Without Delay		
	Zero years	One year	Two years
Free Entry			
Zero years	0.6333	0.0000	0.0000
One year	0.0174	0.2204	0.0200
Two years	0.0068	0.0030	0.0991

Notes: Based on the model estimated under the assumption that students believe future GPA thresholds follow a uniform distribution with a lower and upper bound corresponding to the minimum and maximum GPA threshold observed in the period between 1979 and 1986.
The joint distribution of delay in the "Free Entry" and "Free Entry Without Delay" counterfactuals is reported. "Free Entry" means there are no restrictions on any program in any period. Under the "Free Entry with no Delay" counterfactual there are no restrictions if students enter university directly from university, but if they delay they face the usual model restrictions after one or two years of delay.

Table I.10: Counterfactual Admissions Constraints: Distribution of Field of Study-Using Beliefs about GPA Thresholds that Follow a Uniform Distribution with Maximum Variance (Standard Errors in Parentheses)

	Baseline	**Free Entry**	**Free Entry Except Med.**
Humantities	0.1479	0.1202	0.1393
Natural Science	0.1853	0.1493	0.1823
Social Science	0.3665	0.3531	0.4074
Engineering	0.2291	0.1675	0.2006
Medical programs	0.0713	0.2098	0.0704

Notes: Based on the model estimated under the assumption that students believe future GPA thresholds follow a uniform distribution with a lower and upper bound corresponding to the minimum and maximum GPA threshold observed in the period between 1979 and 1986.
Distributions of field of study are simulated under different counterfactual admissions constraints. The baseline specification uses the model admissions constraints. "Free Entry" means there are no restrictions on any program in any period. "Free Entry Except Med." means there are no restrictions in any period in every other program except Medical programs, for which the model restrictions apply in every year.

Table I.11: Model Estimation Results-Using Beliefs about GPA Thresholds that Follow a Uniform Distribution with Maximum Variance (Standard Errors in Parentheses)

Value of Schooling			
Father holds Candidature in same field of study	12.578 (1.344)	Program located in own city	10.031 (1.073)
Mother holds Candidature in same field of study	6.315 (1.717)	Program located in own region	27.168 (2.327)
Gender match with field of study	22.932 (2.003)	HS track match with field of study	11.028 (1.027)
Student-teacher Ratio	1.187 (0.128)		
Field of study intercepts, relative to Humanities			
Natural sciences	-2.038 (0.740)	Social sciences	0.139 (0.703)
Engineering	10.016 (1.254)	Medical programs	12.857 (1.419)
Value of Delaying			
Local youth unemployment rate	9.408 (4.344)	Age	-0.805 (0.075)
Female, first year	5.602 (0.786)	Female, second year	0.281 (0.799)
Math track, first year	-10.765 (1.067)	Math track, second year	-7.612 (0.944)
Cohort intercepts, relative to 1984			
1981	-1.202 (0.603)	1982	-1.801 (0.595)
1983	-2.156 (0.599)		
Preference shocks			
$\exp(\tau)$	2.884 (0.085)		

Notes: Estimates are from the mdoel that assumes students believe future GPA thresholds follow a uniform distribution with a lower and upper bound corresponding to the minimum and maximum GPA threshold observed in the period between 1979 and 1986.
A student's gender matches with their field of study if the majority in the field are of the same gender. Medicine and Humanities are coded as female, and Natural Sciences, Social Sciences, and Engineering are coded as male. The analogous is true for "gender match with high school (HS) track". Medicine, Natural Sciences, and Engineering are coded as math track fields, while Humanities and Social Sciences are coded as language track fields.

Uniform Beliefs with Drift

To calibrate the beliefs using a uniform distribution with drift, for each program, we regress the Group II thresholds on a linear trend using the data from 1979 to 1986. We extract the parameter on the trend, as well as the standard deviation of the residuals from those regressions. We then assume that students believe the mean of the distribution changes over time according to the trend. They believe that the thresholds are uniformly distributed using as the bounds one residual standard deviation above and below the mean. Students do not update their expectations between periods.

Table I.12: Uniform with Drift Beliefs: Drift Parameter and Residual Standard Deviation, 1979-1986

	Drift Parameter	**Residual St. Dev.**
University of Copenhagen		
Medicine	0.195	0.116
Natural Sciences	-0.007	0.069
Biology	0.308	0.438
Theology	0.008	0.373
Humanities	0.086	0.319
Law	0.143	0.121
Business/Economics	0.027	0.274
Political Science	0.117	0.503
Aarhus University		
Medicine	0.229	0.123
Natural Sciences	0	0
Biology	0.455	0.42
Theology	0	0
Humanities	0.185	0.253
Law	0.156	0.129
Social Sciences	0.133	0.462
Business/Economics	0	0
University of Southern Denmark		
Natural Sciences	0	0
Medicine	0.212	0.125
Humanities	0	0
Business/Economics	0.025	0.087
Roskilde University		
Natural Sciences	0	0
Humanities	0	0
Social Sciences	-0.102	0.563
University of Aalborg		
Engineering	0.05	0.173
Humanities	0	0
Social Sciences	0	0
Danish Technical University		
Electrical Engineering	0.039	0.377
Engineering	0	0
Aarhus Business School		
Business/Economics	0.167	0.525
Copenhagen Business School		
Business/Economics	-0.01	0.104

Notes: The drift parameter is estimated by regressing the Group II GPA threshold on a linear trend. The regressions are run separately for each program in the data from 1979 to 1986. The standard deviations reported in the second column are based on the residuals from these regressions. The programs with zeros for the drift parameter and the standard deviation had no minimum GPA threshold during the period of 1979 to 1986.

Table I.13: Counterfactual Admissions Constraints: Distribution of Delay-Using Beliefs about GPA Thresholds that Follow a Uniform Distribution with Drift (Standard Errors in Parentheses)

	Baseline	**Free Entry**	**Free Entry with no delay**	**Free Entry Except Med.**
0 years delay	0.5406	0.6364	0.6464	0.6727
1 year delay	0.2972	0.2580	0.2307	0.2274
2 years delay	0.1622	0.1056	0.1229	0.0999

Notes: Based on the model estimated under the assumption that students believe future GPA thresholds are uniformly distributed with a mean that follows a non-stochastic trend.
Distributions of delays are simulated under different counterfactual admissions constraints. The baseline specification uses the model admissions constraints. "Free Entry" means there are no restrictions on any program in any period. Under the "Free Entry with no Delay" counterfactual there are no restrictions if students enter university directly from university, but if they delay they face the usual model restrictions after one or two years of delay. "Free Entry Except Med." means there are no restrictions in any period in every other program except Medical programs, for which the model restrictions apply in every year.

Table I.14: Gross flows in the distribution of delay from the baseline to the free entry experiment-Using Beliefs about GPA Thresholds that Follow a Uniform Distribution with Drift

	Free Entry		
	Zero years	One year	Two years
Baseline			
Zero years	0.5345	0.0044	0.0017
One year	0.0641	0.2314	0.0017
Two years	0.0378	0.0222	0.1022

Notes: Based on the model estimated under the assumption that students believe future GPA thresholds are uniformly distributed with a mean that follows a non-stochastic trend.
The joint distribution of delay in the baseline and "Free Entry" counterfactuals is reported. The baseline specification uses the model admissions constraints. "Free Entry" means there are no restrictions on any program in any period.

Table I.15: Gross flows in the distribution of delay from free entry to the free entry without delay experiment-Using Beliefs about GPA Thresholds that Follow a Uniform Distribution with Drift

	Free Entry Without Delay		
	Zero years	One year	Two years
Free Entry			
Zero years	0.6363	0.0000	0.0000
One year	0.0072	0.2291	0.0218
Two years	0.0029	0.0016	0.1012

Notes: Based on the model estimated under the assumption that students believe future GPA thresholds are uniformly distributed with a mean that follows a non-stochastic trend.
The joint distribution of delay in the "Free Entry" and "Free Entry Without Delay" counterfactuals is reported. "Free Entry" means there are no restrictions on any program in any period. Under the "Free Entry with no Delay" counterfactual there are no restrictions if students enter university directly from university, but if they delay they face the usual model restrictions after one or two years of delay.

centering

Table I.16: Counterfactual Admissions Constraints: Distribution of Field of Study-Using Beliefs about GPA Thresholds that Follow a Uniform Distribution with Drift (Standard Errors in Parentheses)

	Baseline	**Free Entry**	**Free Entry Except Med.**
Humantities	0.1579	0.1301	0.1501
Natural Science	0.1837	0.1517	0.1842
Social Science	0.3618	0.3441	0.3960
Engineering	0.2274	0.1692	0.2020
Medical programs	0.0692	0.2050	0.0676

Notes:Based on the model estimated under the assumption that students believe future GPA thresholds are uniformly distributed with a mean that follows a non-stochastic trend.
Distributions of field of study are simulated under different counterfactual admissions constraints. The baseline specification uses the model admissions constraints. "Free Entry" means there are no restrictions on any program in any period. "Free Entry Except Med." means there are no restrictions in any period in every other program except Medical programs, for which the model restrictions apply in every year.

Table I.17: Model Estimation Results-Using Beliefs about GPA Thresholds that Follow a Uniform Distribution with Drift (Standard Errors in Parentheses)

Value of Schooling			
Father holds Candidature in same field of study	17.568	Program located in own city	13.956
	(2.420)		(1.931)
Mother holds Candidature in same field of study	8.639	Program located in own region	38.214
	(2.518)		(4.649)
Gender match with field of study	31.611	HS track match with field of study	14.413
	(3.888)		(1.855)
Student-teacher Ratio	0.615		
	(0.128)		
Field of study intercepts, relative to Humanities			
Natural sciences	-9.264	Social sciences	6.185
	(1.465)		(1.350)
Engineering	8.398	Medical programs	17.164
	(1.616)		(2.481)
Value of Delaying			
Local youth unemployment rate	13.519	Age	-1.217
	(6.438)		(0.153)
Female, first year	7.824	Female, second year	-0.347
	(1.301)		(1.156)
Math track, first year	-16.047	Math track, second year	-12.291
	(2.099)		(1.797)
Cohort intercepts, relative to 1984			
1981	-0.845	1982	0.718
	(0.872)		(0.837)
1983	-2.922		
	(0.907)		
Preference shocks			
$\exp(\tau)$	3.243		
	(0.121)		

Notes: Estimates are from the model that assumes students believe future GPA thresholds are uniformly distributed with a mean that follows a non-stochastic trend.

A student's gender matches with their field of study if the majority in the field are of the same gender. Medicine and Humanities are coded as female, and Natural Sciences, Social Sciences, and Engineering are coded as male. The analogous is true for "gender match with high school (HS) track". Medicine, Natural Sciences, and Engineering are coded as math track fields, while Humanities and Social Sciences are coded as language track fields.

J Four Period Model

We are constrained in the number of periods we can include in our model because the GPA thresholds in 1987 were omitted from the archival reports. This means that when we add a period we lose a cohort of data. We restrict our attention to students who enter after at most two years of delay for this reason. The sample restriction is also motivated by the fact that the GPA multiplier is maximized at 1.18 after two years of delay.

In Table J.1, we show the counts of students who enter university up to 6 years following high school. The sample used to construct Table J.1 includes all high school graduates in the cohorts 1980 to 1984 before any other sample restrictions. Although the mass drops considerably after 2 years of delay, almost 1,200 or nearly 5% delay by three years. To investigate whether omitting these students from our sample changes our results, we extend the model to four periods.

For the four-period model, we use a sample of individuals who graduated high school between 1980 and 1983 and who entered university within three years. We can not use the 1984 cohort for this model. Since the GPA multiplier does not change after two years of delay, students who delay by three years have their GPA inflated by 1.18.

The key findings are not substantially changed by adding a fourth period to the model. In particular, comparing the distribution of delay in the free-entry experiment to the baseline, reported in Table J.2, the fraction of students who delay is reduced by 9.05 percentage points. Again, the reduction in delay in the "no-delay" experiment is slightly larger at 10.9 percentage points. The gross flows from the baseline to free-entry experiment shown in Table J.3 reveal that 13% of the simulated sample reduced their years of delay. This represents 26.6% of the baseline delayers.

Table J.1: Delaying by up to Six Years, Distribution and Sample Counts

Years of Delay	Frequency	Percentage
0	11,446	48.65
1	6,828	29.02
2	3,436	14.61
3	1,169	4.97
4	412	1.75
5	179	0.76
6	55	0.23

Notes: Sample includes all high school graduates in the cohorts 1980 to 1984 who entered the sample programs within 6 years.

Table J.2: Counterfactual Admissions Constraints: Distribution of Delay in a Four Period Model

	Baseline	**Free Entry**	**Free Entry with no delay**	**Free Entry Except Med.**
0 years delay	0.5098	0.6003	0.6184	0.7052
1 year delay	0.2798	0.2524	0.2194	0.1791
2 years delay	0.1476	0.1072	0.1141	0.0837
3 years delay	0.0629	0.0401	0.0480	0.0320

Notes: Distributions of delays are simulated under different counterfactual admissions constraints. The baseline specification uses the model admissions constraints. "Free Entry" means there are no restrictions on any program in any period. Under the "Free Entry with no Delay" counterfactual there are no restrictions if students enter university directly from university, but if they delay they face the usual model restrictions after one or two years of delay. "Free Entry Except Med." means there are no restrictions in any period in every other program except Medical programs, for which the model restrictions apply in every year.

Table J.3: Gross flows in the distribution of delay from the baseline to the free entry experiment in a four period model

	Free Entry			
	Zero years	One year	Two years	Three years
Baseline				
Zero years	0.4991	0.0069	0.0028	0.0010
One year	0.0562	0.2203	0.0024	0.0008
Two years	0.0312	0.0174	0.0980	0.0010
Three years	0.0139	0.0077	0.0039	0.0373

Notes: The joint distribution of delay in the baseline and "Free Entry" counterfactuals is reported. The baseline specification uses the model admissions constraints. "Free Entry" means there are no restrictions on any program in any period.

Table J.4: Gross flows in the distribution of delay from free entry to the free entry without delay experiment

	Free Entry			
	Zero years	One year	Two years	Three years
Baseline				
Zero years	0.6003	0.0000	0.0000	0.0000
One year	0.0118	0.2163	0.0168	0.0075
Two years	0.0046	0.0023	0.0964	0.0038
Three years	0.0016	0.0008	0.0010	0.0368

Notes: The joint distribution of delay in the "Free Entry" and "Free Entry Without Delay" counterfactuals is reported. "Free Entry" means there are no restrictions on any program in any period. Under the "Free Entry with no Delay" counterfactual there are no restrictions if students enter university directly from university, but if they delay they face the usual model restrictions after one or two years of delay.

Table J.5: Counterfactual Admissions Constraints: Distribution of Field of Study in a Four Period Model

	Baseline	**Free Entry**	**Free Entry Except Med.**
Humantities	0.1688	0.1412	0.1627
Natural Science	0.1861	0.1475	0.1802
Social Science	0.3580	0.3460	0.3968
Engineering	0.2063	0.1511	0.1812
Medical programs	0.0808	0.2142	0.0792

Notes: Distributions of field of study are simulated under different counterfactual admissions constraints. The baseline specification uses the model admissions constraints. "Free Entry" means there are no restrictions on any program in any period. "Free Entry Except Med." means there are no restrictions in any period in every other program except Medical programs, for which the model restrictions apply in every year.

K Counterfactual with Known GPA Fluctuations

In the main body of the paper, we simulate a counterfactual in which we remove all admissions restrictions, which also has the coincident effect of removing all risk associated with future GPAs. In this section, we present results from an experiment where the future GPA thresholds are known with certainty in all periods. Students must still take expectations over future preference shocks, but they know what programs are in their future choice sets. Relative to the baseline, this experiment holds constant all aspects of the problem, except the probability weights that are placed on future choice sets. In the baseline, for most students there is risk associated with their eligibility for some subset of the programs. The weight put on a choice set that includes these programs would, therefore, include a sum of probabilities strictly between zero and one. In the "known-GPA" experiment, all of these non-degenerate probabilities would revert to either a zero or a one depending on whether the students own GPA fell above or below the known threshold. Whether this experiment encourages students to increase or decrease their delaying behaviour, depends on three factors. First, it depends on how many risky programs switch to probability one relative to how many switch to probability zero. Second, it depends on the value of the programs for which the probabilities change. Finally, it depends on how close the non-degenerate probabilities, in the baseline, are to 0 or 1.

Overall, the factors tending to discourage delay in the known-GPA experiment dominated. Relative to baseline, in the known-GPA experiment, students are 11.13 percentage points more likely to enter university directly. This is a slightly larger reduction in delay compared to the free-entry experiment, relative to baseline, because almost no students increase their years of delay when the future GPA's are known.

The known-GPA experiment is very different from free-entry, however, because it does not alter the eligibility for programs. As such the overall distribution of field of study is largely unaffected. Thus, we can not interpret the individuals who enter directly in the known-GPA experiment but delay in the baseline as "constrained" by the restrictions, because the restrictions are unaltered.

Table K.1: Known GPA Fluctuations Counterfactual: Distribution of Delay (Standard Errors in Parentheses)

	Baseline	**No GPA Fluctuations**
0 years delay	0.5468	0.6581
	(0.0041)	(0.0037)
1 year delay	0.2937	0.2337
	(0.0031)	(0.0031)
2 years delay	0.1595	0.1081
	(0.0034)	(0.0023)

Notes: Distributions of delays are simulated under different counterfactual admissions constraints. The baseline specification uses the model admissions constraints. Under the "Known GPA Fluctuations" counterfactual there is no uncertainty over future Group II GPA fluctuations. Students know what the future GPA thresholds will be.

Table K.2: Gross flows in the distribution of delay from the baseline to the Known GPA Fluctuations Counterfactual

	No GPA fluctuations		
	Zero years	One year	Two years
Baseline			
Zero years	0.5466	0.0001	0.0000
One year	0.0707	0.2228	0.0002
Two years	0.0408	0.0108	0.1079

Notes: The joint distribution of delay in the baseline and "Known GPA Fluctuations" counterfactuals is reported. The baseline specification uses the model admissions constraints. Under the "Known GPA Fluctuations" counterfactual there is no uncertainty over future Group II GPA fluctuations. Students know what the future GPA thresholds will be.

Table K.3: Known GPA Fluctuations Counterfactual: Distribution of Field of Study (Standard Errors in Parentheses)

	Baseline	**No GPA Fluctuations**
Humantities	0.1475	0.1484
	(0.0023)	(0.0023)
Natural Science	0.1858	0.1890
	(0.0030)	(0.0031)
Social Science	0.3663	0.3638
	(0.0041)	(0.0041)
Engineering	0.2298	0.2295
	(0.0031)	(0.0031)
Medical programs	0.0706	0.0693
	(0.0015)	(0.0015)

Notes: Distributions of field of study are simulated under different counterfactual admissions constraints. The baseline specification uses the model admissions constraints. Under the "Known GPA Fluctuations" counterfactual there is no uncertainty over future Group II GPA fluctuations. Students know what the future GPA thresholds will be.

L Expected Future Income that Does Not Vary with Years of Delay

When we estimate students' expected future incomes, we assume that students expect to earn the average conditional on their observed characteristics, and that those averages vary by groups defined by the intersection of program and years of delay. In this section, we report the results from a model where we assume students do not take into account differences across years of delay. In other words, students expect to earn the conditional group average where the groups are defined only by the programs.

We find that very little changes in this specification. The fraction of students who delay decreases by 9.3 percentage points in the free-entry experiment compared to the baseline. The 12.4% of students reduce their years of delay which represents 27.4% of all baseline delayers.

Table L.1: Counterfactual Admissions Constraints: Distribution of Delay-From Model where Expected Income Does Not Vary with Years of Delay (Standard Errors in Parentheses)

	Baseline	**Free Entry**	**Free Entry with no delay**	**Free Entry Except Med.**
0 years delay	0.5466	0.6394	0.6564	0.6425
	(0.0038)	(0.0044)	(0.0046)	(0.0045)
1 year delay	0.2938	0.2551	0.2243	0.2450
	(0.0020)	(0.0018)	(0.0015)	(0.0017)
2 years delay	0.1596	0.1055	0.1193	0.1125
	(0.0012)	(0.0007)	(0.0009)	(0.0008)

Notes: Distributions of delays are simulated under different counterfactual admissions constraints. The baseline specification uses the model admissions constraints. "Free Entry" means there are no restrictions on any program in any period. Under the "Free Entry with no Delay" counterfactual there are no restrictions if students enter university directly from university, but if they delay they face the usual model restrictions after one or two years of delay. "Free Entry Except Med." means there are no restrictions in any period in every other program except Medical programs, for which the model restrictions apply in every year.

Table L.2: Gross flows in the distribution of delay from the baseline to the free entry experiment-From Model where Expected Income Does Not Vary with Years of Delay

		Free Entry	
	Zero years	One year	Two years
Baseline			
Zero years	0.5369	0.0070	0.0028
One year	0.0648	0.2265	0.0024
Two years	0.0377	0.0215	0.1003

Notes: The joint distribution of delay in the baseline and "Free Entry" counterfactuals is reported. The baseline specification uses the model admissions constraints. "Free Entry" means there are no restrictions on any program in any period.

Table L.3: Gross flows in the distribution of delay from free entry to the free entry without delay experiment-From Model where Expected Income Does Not Vary with Years of Delay

	Free Entry Without Delay		
	Zero years	One year	Two years
Free Entry			
Zero years	0.6394	0.0000	0.0000
One year	0.0123	0.2220	0.0208
Two years	0.0047	0.0023	0.0985

Notes: The joint distribution of delay in the "Free Entry" and "Free Entry Without Delay" counterfactuals is reported. "Free Entry" means there are no restrictions on any program in any period. Under the "Free Entry with no Delay" counterfactual there are no restrictions if students enter university directly from university, but if they delay they face the usual model restrictions after one or two years of delay.

Table L.4: Counterfactual Admissions Constraints: Distribution of Field of Study-From Model where Expected Income Does Not Vary with Years of Delay (Standard Errors in Parentheses)

	Baseline	**Free Entry**	**Free Entry Except Med.**
Humantities	0.1481	0.1210	0.1404
	(0.0011)	(0.0008)	(0.0010)
Natural Science	0.1852	0.1488	0.1831
	(0.0013)	(0.0010)	(0.0013)
Social Science	0.3659	0.3477	0.4018
	(0.0026)	(0.0025)	(0.0029)
Engineering	0.2302	0.1696	0.2050
	(0.0016)	(0.0012)	(0.0014)
Medical programs	0.0705	0.2129	0.0697
	(0.0004)	(0.0015)	(0.0004)

Notes: Distributions of field of study are simulated under different counterfactual admissions constraints. The baseline specification uses the model admissions constraints. "Free Entry" means there are no restrictions on any program in any period. "Free Entry Except Med." means there are no restrictions in any period in every other program except Medical programs, for which the model restrictions apply in every year.

Table L.5: Model Estimation Results-From Model where Expected Income Does Not Vary with Years of Delay (Standard Errors in Parentheses)

Value of Schooling			
Father holds Candidature in same field of study	4.588	Program located in own city	3.669
	(0.398)		(0.318)
Mother holds Candidature in same field of study	2.242	Program located in own region	9.921
	(0.609)		(0.589)
Gender match with field of study	8.394	HS track match with field of study	3.818
	(0.516)		(0.274)
Student-teacher Ratio	0.398		
	(0.128)		
Field of study intercepts, relative to Humanities			
Natural sciences	-1.303	Social sciences	-0.971
	(0.267)		(0.254)
Engineering	2.305	Medical programs	3.764
	(0.367)		(0.405)
Value of Delaying			
Local youth unemployment rate	3.374	Age	-0.295
	(1.583)		(0.021)
Female, first year	2.043	Female, second year	0.094
	(0.260)		(0.292)
Math track, first year	-3.899	Math track, second year	-2.848
	(0.308)		(0.303)
Cohort intercepts, relative to 1984			
1981	-0.569	1982	-0.741
	(0.219)		(0.214)
1983	-0.909		
	(0.214)		
Preference shocks			
$\exp(\tau)$	1.875		
	(0.058)		

Notes: A student's gender matches with their field of study if the majority in the field are of the same gender. Medicine and Humanities are coded as female, and Natural Sciences, Social Sciences, and Engineering are coded as male. The analogous is true for "gender match with high school (HS) track". Medicine, Natural Sciences, and Engineering are coded as math track fields, while Humanities and Social Sciences are coded as language track fields.

M Simple Specification for the Utility of Delaying

In the main model, our specification for the instantaneous utility of delaying includes a number of variables including dummy variables for gender and high school track, age, high school graduation cohort, local unemployment rate, and the expected earnings during the year of the delay. In this Supplemental Appendix, we investigate what effect excluding the variables other than gender and high school track has on our results.

In Table M.1, we report the distribution of delay observed in the estimating sample along side the simulated distribution for this model with a simple specification for the direct utility of delaying. In the simplified model, our in-sample simulations overestimates the propensity to delay by roughly 4 percentage points.

Since these models are estimated using maximum likelihood we can compare the fit of the simple model to the main model using a likelihood ratio test. The sum of the log likelihood function in the main model is -61,465.942 and in the simplified it is -62,087.872. Since the difference in the number of parameters is only 4, the simplified model is easily rejected.

Although the level of delaying is off in the simplified model, the important identification in our model comes from changes in the actual GPA thresholds which are not affected by how we specify the utility of delay. In this section, we also show the tables in which our key findings are reported. The key patterns are still observed. Delay falls by roughly 9 percentage points in the free-entry counterfactual. The fraction of students who reduce their years of delay is 12.23 %, which represents a small fraction of all delayers (24.8%) because this model overestimates delay.

Table M.1: In Sample Data and Simulated Distribution of Delay-From a Model with a Simple Utility of Delay Specification (Standard Errors in Parentheses)

	Data	**Simulated**
0 years delay	0.546	0.5050
	(0.004)	(0.0038)
1 year delay	0.295	0.2978
	(0.003)	(0.0020)
2 years delay	0.158	0.1971
	(0.003)	(0.0012)

Notes:

Table M.2: Counterfactual Admissions Constraints: Distribution of Delay-From a Model with a Simple Utility of Delay Specification (Standard Errors in Parentheses)

	Baseline	**Free Entry**	**Free Entry with no delay**	**Free Entry Except Med.**
0 years delay	0.5050	0.5954	0.6119	0.6040
	(0.0038)	(0.0044)	(0.0046)	(0.0045)
1 year delay	0.2978	0.2622	0.2309	0.2500
	(0.0020)	(0.0018)	(0.0015)	(0.0017)
2 years delay	0.1971	0.1424	0.1572	0.1460
	(0.0012)	(0.0007)	(0.0009)	(0.0008)

Notes: Distributions of delays are simulated under different counterfactual admissions constraints. The baseline specification uses the model admissions constraints. "Free Entry" means there are no restrictions on any program in any period. Under the "Free Entry with no Delay" counterfactual there are no restrictions if students enter university directly from university, but if they delay they face the usual model restrictions after one or two years of delay. "Free Entry Except Med." means there are no restrictions in any period in every other program except Medical programs, for which the model restrictions apply in every year.

Table M.3: Gross flows in the distribution of delay from the baseline to the free entry experiment-From a Model with a Simple Utility of Delay Specification

	Free Entry		
	Zero years	One year	Two years
Baseline			
Zero years	0.4957	0.0067	0.0026
One year	0.0623	0.2328	0.0027
Two years	0.0373	0.0227	0.1371

Notes: The joint distribution of delay in the baseline and "Free Entry" counterfactuals is reported. The baseline specification uses the model admissions constraints. "Free Entry" means there are no restrictions on any program in any period.

Table M.4: Gross flows in the distribution of delay from free entry to the free entry without delay experiment-From a Model with a Simple Utility of Delay Specification

	Free Entry Without Delay		
	Zero years	One year	Two years
Free Entry			
Zero years	0.5954	0.0000	0.0000
One year	0.0119	0.2284	0.0219
Two years	0.0046	0.0026	0.1353

Notes: The joint distribution of delay in the "Free Entry" and "Free Entry Without Delay" counterfactuals is reported. "Free Entry" means there are no restrictions on any program in any period. Under the "Free Entry with no Delay" counterfactual there are no restrictions if students enter university directly from university, but if they delay they face the usual model restrictions after one or two years of delay.

Table M.5: Counterfactual Admissions Constraints: Distribution of Field of Study-From a Model with a Simple Utility of Delay Specification (Standard Errors in Parentheses)

	Baseline	**Free Entry**	**Free Entry Except Med.**
Humantities	0.1455	0.1182	0.1380
	(0.0011)	(0.0008)	(0.0010)
Natural Science	0.1853	0.1498	0.1834
	(0.0013)	(0.0010)	(0.0013)
Social Science	0.3671	0.3515	0.4053
	(0.0026)	(0.0025)	(0.0029)
Engineering	0.2303	0.1684	0.2024
	(0.0016)	(0.0012)	(0.0014)
Medical programs	0.0718	0.2121	0.0709
	(0.0004)	(0.0015)	(0.0004)

Notes: Distributions of field of study are simulated under different counterfactual admissions constraints. The baseline specification uses the model admissions constraints. "Free Entry" means there are no restrictions on any program in any period. "Free Entry Except Med." means there are no restrictions in any period in every other program except Medical programs, for which the model restrictions apply in every year.

Table M.6: Model Estimation Results-From a Model with a Simple Utility of Delay Specification (Standard Errors in Parentheses)

Value of Schooling			
Father holds Candidature in same field of study	13.339	Program located in own city	10.471
	(1.446)		(1.144)
Mother holds Candidature in same field of study	6.890	Program located in own region	28.742
	(1.824)		(2.525)
Gender match with field of study	25.292	HS track match with field of study	13.085
	(2.263)		(1.226)
Student-teacher Ratio	1.172		
	(0.128)		
Field of study intercepts, relative to Humanities			
Natural sciences	-2.771	Social sciences	1.480
	(0.806)		(0.779)
Engineering	9.987	Medical programs	13.995
	(1.302)		(1.554)
Value of Delaying			
Female, first year	-1.577	Female, second year	-12.214
	(0.629)		(1.294)
Math track, first year	-26.166	Math track, second year	-22.631
	(2.298)		(2.045)
Preference shocks			
$\exp(\tau)$	2.934		
	(0.087)		

Notes: A student's gender matches with their field of study if the majority in the field are of the same gender. Medicine and Humanities are coded as female, and Natural Sciences, Social Sciences, and Engineering are coded as male. The analogous is true for "gender match with high school (HS) track". Medicine, Natural Sciences, and Engineering are coded as math track fields, while Humanities and Social Sciences are coded as language track fields.