Participation and efficiency in higher education with ex-post screening

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Introduction

- There is a trade-off between participation and study efficiency in higher education.
  - Governments aim to ensure broad access to a large number of students and minimize drop-out or delay.
  - 62% of young adults in OECD countries enter a university level program but only 39% are expected to complete it (OECD, 2012).
  - Many students drop out without obtaining a degree or obtain their degree after a substantial delay.
- Screening and admission policies influence this trade-off and countries have followed a variety of approaches.
  - Ex-ante screening versus ex-post screening

Research questions

- Analysis of participation and efficiency in higher education in Flanders where there is essentially no ex-ante screening and no tuition fees but highly selective ex-post screening.

- Evaluation of the effects of alternative, ex-ante admission policies on participation and study efficiency.

Overview of the presentation

- Admission policies and study efficiency in OECD countries
- Higher education in Flanders
- Dynamic discrete choice model
- Empirical results and policy counterfactuals
- Conclusion

Admission policies and study efficiency

Table 1: Admission policies and study efficiency

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

Notes: Entry and graduation rates are obtained from OECD (2012). They are expressed in percentages of an age cohort. Efficiency is calculated as the percentage of university graduates divided by the percentage of university entrants.

Admission policies and study efficiency

- OECD countries follow a variety of admission policies.
- Ex-ante screening does not lead to low participation.
- Study efficiency is highest in countries that follow ex-ante screening policies.

Higher education in Flanders

- All high school graduates are entitled to start at most higher education programs at college or university.
- Tuition fees are low and capped at 593,3 EUR.
- Policy of low tuition fees and ex-post screening results in low study efficiency:
  - Low success rates in the first year of higher education (on average 50%).
  - Many students drop out or reorient after the first year.
  - Only 38% of the first year students of 2001 obtained a degree in higher education within the minimal required time.
  - Another 28% obtained a degree with at least 1 year of delay.

Dynamic discrete choice model

Model setup

- In each period, students choose a major and institution or choose for the dropout option.
- Students who choose for the dropout option start working and earn the dropout specific wage.
- At the end of each period, students observe whether they succeeded or not.
- Conditional upon the results in the previous period, students update their choice.
- Once a student has accumulated 3 credits, he graduates and starts working and earns the wage corresponding to his degree.

Dynamic discrete choice model

Utility of studying

- Utility of studying option j in period t

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

- with:
  - S_0 a vector of personal characteristics
  - X_t the number of course credits in period t
  - d_{t-1} the option chosen in the previous period
  - C^j the cost of attending option j

Dynamic discrete choice model

Value functions

1) The value of working after graduation in option j

$$V_t^j(S_0) = \alpha_5 \sum_{t=1}^{40} \delta^{t-1} \widehat{w}_t^j$$

- $\widehat{w}_t^j$ the expected wage in period t after graduating in option j.
- δ the discount factor

2) The value of studying option j, define $\Phi_t = (S_0, d_{t-1}, C^j, t)$

$$\begin{aligned} V_t^j(\Phi_t, X_t) &= u_t^j(\Phi_t, X_t) \\ &\quad + \delta\left[\widehat{\lambda}_t^j \widetilde{V}_{t+1}(\Phi_{t+1}, X_t+1) + (1-\widehat{\lambda}_t^j)\widetilde{V}_{t+1}(\Phi_{t+1}, X_t)\right] \end{aligned}$$

- $\widehat{\lambda}_t^j$ the expected probability of success in option j
- $\widetilde{V}_{t+1}$ the expected value function from period $t+1$ onwards

- Conditional independence and i.i.d. assumptions imply that there exists a closed form solution for the choice probabilities given by the dynamic logit formula:

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

- Furthermore, the expected value function $\widetilde{V}_{t+1}$ can be written as:

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

- Arcidiacono and Miller (2010) show that the expected value can be expressed as a function of the value of choosing one option and the conditional probability of choosing this option.

- Case 1: Not sufficient credits to graduate:

$$\widetilde{V}_{t+1}(\Phi_{t+1}, X_{t+1}) = \gamma + V^0_{t+1}(\Phi_{t+1}, X_{t+1}) - \log(\Pr(d^0_{t+1} = 1 | \Phi_{t+1}, X_{t+1}))$$

- Case 2: Sufficient credits to graduate:

$$\begin{aligned}
\widetilde{V}_{t+1}(\Phi_{t+1}, X_t) &= \gamma + V^0_{t+1}(\Phi_{t+1}, X_t) - \log(\Pr(d^0_{t+1} = 1 | \Phi_{t+1}, X_t)) \\
\widetilde{V}_{t+1}(\Phi_{t+1}, X_t + 1) &= \alpha_5 \sum_{t=1}^{40} \delta^{t-1} \widehat{w}^j_t
\end{aligned}$$

Dynamic discrete choice model

Unobserved heterogeneity and estimation

- Account for unobserved heterogeneity by introducing a fixed number of discrete types who differ in preferences and ability.
  - Flexible correlation of the error terms across alternatives.
  - Correlation of unobserved preferences and ability over time.

- EM algorithm simplifies estimation of the model.
  1. Expectation step: Update the probability of being in each unobserved state.
  2. Maximization step: Given the type probabilities, maximize the joint log likelihood of choices and study success.
  3. Repeat this algorithm until convergence.

- Model can be estimated by using the 2 step procedure developed by Arcidiacono and Miller (2010) for dynamic discrete choice models.

- Step 1:
  - OLS regression for wages.
  - Flexible logit regression for the probability of dropout.
  - Flexible logit regression for the probability of success.

- Step 2:
  - Estimate the dynamic discrete choice model using the results from the first step.

Empirical results

The probability of success

Table 2: The probability of success

Period	credits	Coefficient	St. error
period 2	0	0.395*	(0.044)
	1	1.781*	(0.052)
period 3	0	0.234*	(0.079)
	1	1.353*	(0.058)
	2	3.182*	(0.096)
period 4	0	0.012	(0.166)
	1	0.981*	(0.086)
	2	2.273*	(0.084)
period 5	0	-1.598*	(0.395)
	1	-0.242	(0.141)
	2	1.190*	(0.094)
period 6	0	-1.929*	(0.595)
	1	-0.566*	(0.225)
	2	0.352*	(0.146)

Note: * statistical significance at 5% level.
Base category = 0 credits in period 1

Empirical results

The probability of success

Table 2: The probability of success (continued)

	SCI UNIV		SSCI UNIV		BIOM UNIV		ARTS UNIV	
	Coef.	St. error	Coef.	St. error	Coef.	St. error	Coef.	St. error
constant type 1	-0.444	(0.329)	-4.347*	(0.448)	-1.459*	(0.559)	-1.163*	(0.285)
constant type 2	-2.734*	(0.422)	-0.657*	(0.244)	-3.822*	(0.600)	-4.034*	(0.455)
male	-0.452*	(0.151)	-0.477*	(0.080)	-0.684*	(0.146)	-0.476*	(0.146)
general HS[a]								
clas + math	0.944*	(0.319)	0.961*	(0.245)	2.171*	(0.558)	1.632*	(0.294)
clas + lang	0.401	(0.614)	0.555*	(0.248)	2.071*	(0.651)	1.930*	(0.278)
sci + math	1.001*	(0.302)	0.942*	(0.246)	2.240*	(0.548)	1.153*	(0.319)
math + lang	0.441	(0.375)	0.510*	(0.253)	1.434*	(0.583)	1.360*	(0.300)
econ + math	-0.147	(0.415)	0.780*	(0.249)	2.124*	(0.683)	1.830*	(0.471)
econ + lang	-0.436	(0.765)	0.289	(0.248)	1.161	(0.814)	0.454	(0.285)
human	0.307	(0.762)	0.297	(0.260)	-0.242	(1.210)	0.658*	(0.299)
repeated	-0.701*	(0.250)	-0.377*	(0.112)	-0.881*	(0.233)	-0.553*	(0.179)
catholic HS	0.231	(0.171)	0.389*	(0.104)	0.305	(0.177)	0.564*	(0.180)

Note: standard errors in parentheses; * statistical significance at 5% level.
[a] Base category = technical, artistic or vocational secondary education

Empirical results

The probability of success

Table 2: The probability of success (continued)

	SCI COLL		SSCI COLL		BIOM COLL		ARTS COLL	
	Coef.	St. error	Coef.	St. error	Coef.	St. error	Coef.	St. error
constant type 1	-0.274	(0.368)	-1.135*	(0.128)	-0.274	(0.368)	-0.262	(0.497)
constant type 2	-1.975*	(0.411)	-2.189*	(0.136)	-1.975*	(0.411)	-1.013*	(0.533)
male	-0.599*	(0.139)	-0.675*	(0.050)	-0.599*	(0.139)	-0.413*	(0.158)
general HS[b]								
clas + math	1.745*	(0.451)	3.225*	(0.230)	1.745*	(0.451)	0.541	(0.495)
clas + lang	1.275*	(0.508)	2.747*	(0.177)	1.275*	(0.508)	1.100*	(0.523)
sci + math	2.312*	(0.410)	2.836*	(0.165)	2.312*	(0.410)	1.180*	(0.594)
math + lang	1.718*	(0.408)	2.569*	(0.159)	1.718*	(0.408)	0.893	(0.526)
econ + math	0.976*	(0.458)	2.239*	(0.150)	0.976*	(0.458)	0.933	(0.773)
econ + lang	0.957*	(0.393)	2.086*	(0.132)	0.957*	(0.393)	0.171	(0.499)
human	0.491	(0.377)	1.860*	(0.139)	0.491	(0.377)	0.449	(0.515)
technical HS[b]								
business	0.207	(0.420)	1.308*	(0.130)	0.207	(0.420)	-0.238	(0.579)
sci + tech	0.855*	(0.373)	1.399*	(0.165)	0.855*	(0.373)	0.785	(0.866)
social + tech	0.421	(0.369)	1.177*	(0.146)	0.421	(0.369)	-0.247	(0.837)
technics	0.979*	(0.421)	0.939*	(0.184)	0.979*	(0.421)	0.438	(0.652)
other tech	0.358	(0.365)	1.040*	(0.137)	0.358	(0.365)	0.198	(0.630)
artistic HS[b]	0.773	(0.609)	0.904*	(0.228)	0.773	(0.609)	0.369	(0.489)
repeated	-0.488*	(0.099)	-0.447	(0.050)	-0.594*	(0.130)	-0.441	(0.165)
catholic HS	0.195*	(0.099)	0.255*	(0.058)	0.265	(0.161)	0.030	(0.169)

Note: standard errors in parentheses; * statistical significance at 5% level.

[b] Base category = vocational secondary education

Empirical results

Dynamic discrete choice model

Table 3: Dynamic discrete choice model

	SCI UNIV[a]		SSCI UNIV[a]		BIOM UNIV[a]		ARTS UNIV[a]	
	Coef.	St. error	Coef.	St. error	Coef.	St. error	Coef.	St. error
constant type 1	-5.133*	(0.152)	-4.758*	(0.122)	-4.610*	(0.197)	-3.626*	(0.119)
constant type 2	-8.381*	(0.196)	-5.147*	(0.098)	-7.767*	(0.227)	-6.360*	(0.173)
male	0.933*	(0.099)	0.041	(0.061)	-0.280*	(0.099)	-0.090	(0.088)
general HS[a]								
clas + math	5.219*	(0.197)	2.853*	(0.143)	5.188*	(0.238)	4.093*	(0.184)
clas + lang	3.483*	(0.315)	2.993*	(0.144)	3.530*	(0.292)	4.645*	(0.189)
sci + math	5.567*	(0.169)	2.395*	(0.124)	5.496*	(0.216)	3.445*	(0.183)
math + lang	3.816*	(0.212)	2.578*	(0.136)	3.973*	(0.245)	3.229*	(0.175)
econ + math	3.296*	(0.234)	3.128*	(0.140)	2.238*	(0.284)	1.554*	(0.218)
econ + lang	1.584*	(0.341)	2.326*	(0.115)	1.417*	(0.324)	2.714*	(0.154)
human	1.300*	(0.360)	2.426*	(0.125)	1.915*	(0.407)	2.391*	(0.165)
repeated	-0.798*	(0.136)	-0.013	(0.072)	-0.332	(0.142)	0.028	(0.102)

Note: standard errors in parentheses; * statistical significance at 5% level.

[a] Base category = drop-out option

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

Table 3: Dynamic discrete choice model (continued)

	SCI COLL[a]		SSCI COLL[a]		BIOM COLL[a]		ARTS COLL[a]	
	Coef.	St. error	Coef.	St. error	Coef.	St. error	Coef.	St. error
constant type 1	-3.859*	(0.164)	-1.657*	(0.069)	-3.260*	(0.159)	-4.320*	(0.213)
constant type 2	-5.688*	(0.174)	-2.938*	(0.074)	-5.507*	(0.149)	-6.215*	(0.232)
male	0.935*	(0.072)	0.042	(0.044)	-0.811*	(0.080)	-0.130	(0.091)
general HS[b]								
clas + math	3.146*	(0.218)	0.572*	(0.140)	3.285*	(0.233)	3.453*	(0.303)
clas + lang	1.811*	(0.294)	1.253*	(0.131)	2.987*	(0.268)	4.396*	(0.260)
sci + math	3.592*	(0.185)	1.068*	(0.109)	3.500*	(0.196)	3.016*	(0.279)
math + lang	3.000*	(0.207)	1.385*	(0.116)	3.283*	(0.207)	3.880*	(0.253)
econ + math	2.542*	(0.217)	1.637*	(0.124)	2.661*	(0.240)	2.082*	(0.341)
econ + lang	1.930*	(0.199)	1.742*	(0.090)	2.532*	(0.194)	3.505*	(0.234)
human	2.282*	(0.217)	1.536*	(0.097)	2.963*	(0.196)	3.061*	(0.243)
technical HS[b]								
business	1.519*	(0.187)	1.478*	(0.081)	1.581*	(0.205)	1.910*	(0.261)
sci + tech	2.284*	(0.177)	0.471*	(0.106)	2.592*	(0.190)	0.469	(0.379)
social + tech	2.187*	(0.244)	1.857*	(0.103)	3.387*	(0.193)	2.002*	(0.371)
technics	2.328*	(0.167)	0.044	(0.103)	1.715*	(0.202)	1.046*	(0.294)
other tech	1.192*	(0.209)	1.239*	(0.086)	2.441*	(0.180)	1.332*	(0.289)
artistic HS[b]	2.376*	(0.206)	0.279	(0.144)	0.954*	(0.297)	3.476*	(0.235)
repeated	-0.136*	(0.065)	0.002	(0.044)	-0.115	(0.078)	0.168	(0.095)

Note: standard errors in parentheses; * statistical significance at 5% level.

[a] Base category = drop-out option

[b] Base category = vocational secondary education

Empirical results

Dynamic discrete choice model

Table 3: Dynamic discrete choice model (continued)

Option[c]	Variable	Coefficient	St. error
SCI	lagSSCI	-4.021*	(0.113)
	lagBIOM	-4.402*	(0.158)
	lagARTS	-4.925*	(0.219)
SSCI	lagSCI	-2.489*	(0.081)
	lagBIOM	-3.371*	(0.098)
	lagARTS	-2.793*	(0.088)
BIOM	lagSCI	-3.038*	(0.133)
	lagSSCI	-3.529*	(0.114)
	lagARTS	-5.024*	(0.277)
ARTS	lagSCI	-3.129*	(0.189)
	lagSSCI	-3.115*	(0.121)
	lagBIOM	-4.786*	(0.324)
UNIV	lagCOLL	-5.963*	(0.118)
COLL	lagUNIV	-0.908*	(0.049)
credits		1.456*	(0.036)
cost		-0.363*	(0.005)
earnings		0.013*	(0.000)
type 1		48.3%	
type 2		51.7%	
	β	0.95	(0)

Note: standard errors in parentheses
* statistical significance at 5% level
[c] Base category = same option in the previous period

Empirical results

Conclusions from regressions

- The probability of success:
  - Males obtain on average lower success rates.
  - High school background determines success.
  - Students who already obtained some credits face higher success rates.
  - Type 1 individuals have higher success rates in all options, except at SSCI at university.
- Dynamic discrete choice model:
  - Gender and high school background determine choices.
  - Students who already obtained some credits are more likely to continue studying.
  - Switching costs are significant and differ beween programs.
  - Distance has a negative effect on choices.
  - Type 1 individuals are more likely to participate in higher education.

Policy counterfactuals

The estimates of the model can be used to evaluate the effects of alternative admission policies.

1. Entry exams in all programs, only students with an expected probability of success of at least 50% are allowed to start.
2. Similar entry exam, but only at university.
3. Policy 1 but lower admission standard of 40%.
4. Policy 2 but lower admission standard of 40%.
5. Admission on the basis of high school program at university.

Policy counterfactuals

Table 4: Predictions and policy counterfactuals

	observed	status quo	entry exam				admission on HS program at university
			50% success rate threshold		40% success rate threshold		
			all programs	university	all programs	university	
Participation in HE	65.2	63.7	-22.6	-2.2	-13.6	-1.4	-0.8
college	43.3	43.3	-14.6	+6.2	-8.2	+4.2	+1.6
univ	21.9	20.4	-8.0	-8.4	-5.4	-5.6	-2.4
Success in period 1	31.7	31.0	-5.4	+1.1	-2.0	+1.2	+0.2
college	20.5	21.1	-3.2	+3.6	-0.9	+2.4	+0.9
univ	11.2	9.9	-3.5	-2.5	-1.1	-1.2	-0.7
Dipl after 3 years	25.0	21.5	-1.6	+1.0	+0.1	+0.9	+0.1
college	15.4	14.8	-0.9	+1.8	+0.3	+1.2	+0.3
univ	9.6	6.7	-0.7	-0.8	-0.2	-0.3	-0.2
Dipl after 6 years	43.6	34.7	-4.3	+1.3	-0.4	+1.3	+0.3
college	29.4	24.0	-2.9	+2.9	0	+1.8	+0.5
univ	14.2	10.7	-1.4	-1.6	-0.4	-0.5	-0.2

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

Policy counterfactuals

- Entry exams in all programs with a 50% threshold will decrease participation but the number of graduates will also decrease.
- Lowering the threshold will still substantially decrease participation but the number of graduates will only slightly decrease.
- Entry exams at university will increase study efficiency in higher education. Participation will slightly decrease, with a large shift from universities to college, but the number of graduates will increase.
- Admission on the basis of high school program at universities has similar effects as an entry exam.

Conclusion

- There is a trade-off between participation and study efficiency in higher education.
- This trade-off is illustrated for Flanders where there is essentially no ex-ante screening but highly selective ex-post screening.
- We find that a suitably designed ex-ante screening system at university programs can increase the study efficiency in higher education without substantially reducing the overall participation.