Optimal Dynamic Selection Under Costly Evaluation: Evidence from Graduate Admissions

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Motivation

- **Economic Problem:** Selecting best options under costly evaluation
  - Determining each option's true quality costs decision-maker time and effort
  - Low-cost screening of all options $\Rightarrow$ high-cost evaluation of surviving options
  - **Examples:** Admissions and hiring, clinical trials, matching platforms
- **Why Graduate Admissions:** Benefits graduate programs and future applicants
  - Graduate programs invest time and money into students' development
  - If programs were undervaluing applicants with certain characteristics, future such applicants may receive formerly-withheld opportunities

Research Questions

1. Which factors in applications affect admission and success in graduate school?
   - Literature measures success with program completion and job placement ranking
2. Are admissions committees optimizing, or are they making mistakes?
   - Goal is to accept applicants with highest success probabilities who will matriculate
   - Predictors of admission only (success only) may be overvalued (undervalued)
3. If they are making mistakes, how can they make better admissions decisions?
   - In turn, by changing decision rules, how much better of a cohort can they admit?

★ This paper's methods generalize to admissions, hiring, and other settings

Methodology and Main Results

- Build structural models of admissions committee's decision problem that support:
  - Statistical tests of whether committee's decision rule aligns with desired objective
  - Counterfactual simulations quantifying gains from deviating to model's decision rule
- Estimate model parameters with admissions data from a major research university
  - Do estimated success probabilities align with those implied by committee's decisions?
  - Tests reject optimality and counterfactual deviation gains statistically significant when committee misvalues applicant characteristics, but not when it optimizes

Literature Review

- **Graduate Admissions:** Regress acceptance and success on applicant charateristics
  - **Original Literature:** Attiyeh & Attiyeh (1997); Krueger & Wu (2000); Grove & Wu (2007); Athey, Katz, Krueger, Levitt & Poterba (2007)
  - **Study of 2002 Cohort:** Stock, Finegan & Siegfried (2006–2015)
  - **New Predictors/Methods:** Bai, Esche, MacLeod & Shi (2022)
- **Optimal Dynamic Selection Under Costly Evaluation:**
  - **Sequential Search:** McCall (1970); Mortensen (1970); Weitzman (1979)
  - **Rational Inattention:** Sims (2003); Matějka & McKay (2015); Caplin & Dean (2015)

★ **This Paper:** Builds and estimates dynamic selection models of admissions, which test optimality by relating acceptance effects to success effects

Synthetic Data Protocol (IRB-Approved)

1. **Administrative office receives data from university departments**
   - Algorithmically extracts variables from textual files, such as recommendation letters
2. **Synthetic data (Patki et al. 2016) used for model development**
   - Estimate joint distribution of variables, and simulate synthetic dataset from it
   - Rows do not correspond to real subjects, preventing identity disclosure
   - Cells with < 5 comparable observations binned to prevent attribute disclosure
3. **Administrative office executes final estimation code on actual data**
   - Only summary statistics and parameter estimates are returned to researcher

★ **Contribution:** Privacy-protecting framework for researchers studying sensitive data

Synthetic Data Example

Outline

Data Description

- **Sample:** Applicants to research university's economics, government, history, linguistics, and psychology PhD programs from 2015 to 2023
- **Dependent Variables:** Measures of admission and success
  - **Admission:** Indicators for all stages of admissions process, including waitlist
  - **Success:** Completion and placement category/quality for **all** applicants, with academia-equivalent rankings for non-academic placements (Krueger & Wu 2000)
- **Independent Variables:** Objective vs. subjective
  - **Objective:** Demographics and performance measures, such as GRE scores
  - **Subjective:** Textual processing of recommendation letters, application essays, CVs, and supplemental forms using dictionaries to construct variables

Variables | Inference vs. Prediction | Sample Selection

Reduced-Form Summary

- **Data:** All applicants to all 5 graduate programs from 2020 to 2023
  - Currently have results for acceptance and objective variables only
  - Implementing synthetic data protocol to complete the empirical work
- **Method:** Logistic regressions with lasso for variable selection
- **Results:** Economics admissions cares most about quantitative GRE and undergraduate GPA, and is most data-driven based on goodness of fit
  - Need success data to see if other programs are making mistakes
  - Prolific recommenders increase acceptance probability $\Rightarrow$ network effects

Summary Statistics | Summary Statistics (Matriculation)

Post-Lasso AMEs: Predicting Acceptance

Dependent Variable = Accept	Economics	Government	History	Linguistics	Psychology
GRE Verbal Percentile	0.0012***	0.0013**	0.0032***		0.0022**
GRE Quantitative Percentile	0.0119***	0.0006*	0.0019***	0.0009	
GRE Analytic Percentile	0.0014***	0.0009**		0.0009	
Undergraduate GPA	0.1710***	0.0267	0.0985**	0.0499	
TOEFL/IELTS	0.0299	0.0254	0.0758*	0.0474	
Elite U.S. University	0.0635***	0.0144	0.0452*		0.0346
Elite U.S. Liberal Arts College	0.0806***	0.0247*	0.0771**		0.0604
Elite Foreign University	0.0365*		0.0432	0.0535	
Graduate Degree			0.0210		
Work Experience	0.0293**	0.0157	0.0383		0.0722**
#Professor Recommenders			0.0436**	0.0259*	
#Prolific Recommenders	0.0209***	0.0115**	0.0160	0.0184**	0.0195
#Math Courses	0.0131***				
Advanced Math	0.0180				
Pseudo-R2	0.2671	0.1500	0.1847	0.1722	0.1844

▸▸ Full Post-Lasso AMEs ▸▸ Logistic Regression AMEs ▸▸ Logistic Regression Results (Matriculation)

Acceptance vs. Success AMEs

Program = Economics	Accept	Success
GRE Verbal Percentile	0.0012***	
GRE Quantitative Percentile	0.0119***	
GRE Analytic Percentile	0.0014***	
Undergraduate GPA	0.1710***	
TOEFL/IELTS	0.0299	
Elite U.S. University	0.0635***	
Elite U.S. Liberal Arts College	0.0806***	
Elite Foreign University	0.0365*	
Work Experience	0.0293**	
#Prolific Recommenders	0.0209***	
#Math Courses	0.0131***	
Advanced Math	0.0180	

- Admissions literature regresses acceptance and success on variables in applications, and qualitatively compares the effects
- While such comparisons are of interest, they are insufficient to test optimality
- Need model of admissions to relate acceptance effects to success effects

Insufficiency of Comparing AMEs

Outline

Why Structural Models?

- **Reason 1:** Test whether committee's decision rule aligns with desired objective
  - Per literature, committee should accept applicants with highest success probabilities
  - Committees also accept applicants with higher matriculation probabilities
- **Reason 2:** Find counterfactual decision rule in which committee optimizes
  - Quantify gains from deviating from actual to counterfactual decision rule

Model Framework

- **Portfolio Choice Problem:** Accept subset of applicants with highest sum of success probabilities subject to capacity constraint on number of acceptances
- For each applicant $n \in \{1, \ldots, N\}$, make decision $d_n \in \{\text{Accept}, \text{Reject}\}$ given:

$$\max_{(d_1,\ldots,d_N)\in\{A,R\}^N} \sum_{n=1}^{N} \underbrace{P(y_n = S|x_n, z_n)}_{\text{Success probability}} \underbrace{\mathbb{1}(d_n = A)}_{\text{Acceptance}}, \text{ such that: } \sum_{n=1}^{N} \underbrace{\mathbb{1}(d_n = A)}_{\text{Acceptance}} \leq N_A,$$

where x = objective variables, z = subjective variables, $y \in \{\text{Success}, \text{Failure}\}$, N = number of applicants, and N_A = maximum number of acceptances

Model Framework

- **Portfolio Choice Problem:** Accept subset of applicants with highest sum of success probabilities subject to capacity constraint on number of acceptances

$$\max_{(d_1,\ldots,d_N)\in\{A,R\}^N} \sum_{n=1}^{N} \underbrace{P(y_n = S|x_n, z_n)}_{\text{Success probability}} \underbrace{\mathbb{1}(d_n = A)}_{\text{Acceptance}}, \text{ such that: } \sum_{n=1}^{N} \underbrace{\mathbb{1}(d_n = A)}_{\text{Acceptance}} \leq N_A$$

- BEMS (2022) prove that portfolio choice problem reduces to cutoff rule problem
  - Accept applicant if and only if their success probability exceeds cutoff probability
  - Decisions across applicants now independent, so no need to consider all subsets

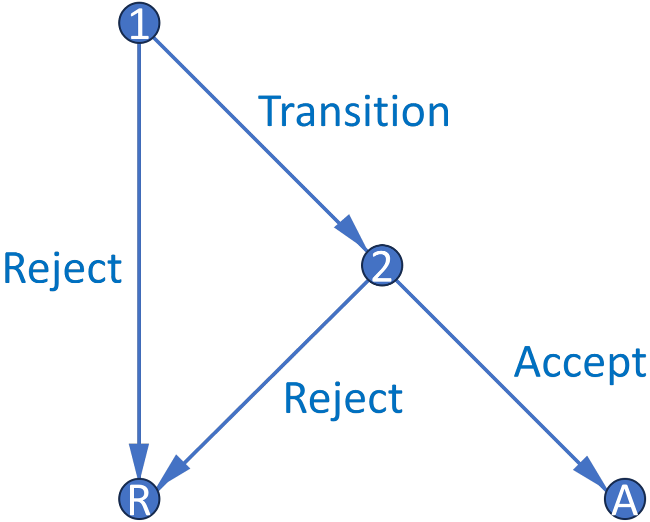
Portfolio Choice to Cutoff Rule

Cutoff Rule Problem

- Start with two-round cutoff rule problem that accounts for costly evaluation:
  - **Round 1:** See only objective variables (e.g. GRE). Can transition application file to Round 2 to see subjective variables (e.g. recommendation letters), or can reject
  - **Round 2:** If chose to transition application file in Round 1, can accept or reject
  - Assume for now committee transitions and accepts optimal number of files
- Along with the baseline dynamic model, there are two additional models
  - Static model makes it possible to compare cutoff probabilities across rounds
  - Waitlist model adds a third round and accounts for matriculation probabilities

Models of Admissions

Decision Graph



Dynamic Model

- **States:** r = round, x = objective variables, z = subjective variables, t = year, ϵ_r = Type 1 extreme value preference shock with scale parameter σ
- **Controls:** $d_1 \in \{\text{Transition}, \text{Reject}\}$, $d_2 \in \{\text{Accept}, \text{Reject}\}$
- **Outcomes:** $y \in \{\text{Success}, \text{Failure}\}$, y_r^* = marginal outcome

Dynamic Parameterization

Dynamic Model

- **States:** r = round, x = objective variables, z = subjective variables, t = year, ϵ_r = Type 1 extreme value preference shock with scale parameter σ
- **Controls:** $d_1 \in \{\text{Transition}, \text{Reject}\}$, $d_2 \in \{\text{Accept}, \text{Reject}\}$
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Round 2:

$$v_2(x, z, t, \epsilon_2) = \max_{d_2 \in \{A,R\}} u_2(x, z, t, d_2) + \epsilon_2(d_2), \text{ such that:}$$

$$u_2(x, z, t, d_2) = \underbrace{P(y = S|x, z)\mathbb{1}(d_2 = A)}_{\text{If accept, get } P(\text{Success})} + \underbrace{P(y_2^* = S|t)\mathbb{1}(d_2 = R)}_{\text{If reject, get } P(\text{Cutoff})}$$

Dynamic Parameterization

Dynamic Model

Round 1:

$$v_1(x, t, \epsilon_1) = \max_{d_1 \in \{T,R\}} u_1(x, t, d_1) + \epsilon_1(d_1), \text{ such that:}$$

$$u_1(x, t, d_1) = \underbrace{\mathbb{E}[v_2(x, z, t, \epsilon_2)|x, t]\mathbb{1}(d_1 = T)}_{\text{If transition, get } \mathbb{E}[\text{Social Surplus}]} + \underbrace{L(y_1^* = S|t)\mathbb{1}(d_1 = R)}_{\text{If reject, get } L(\text{Cutoff})}, \text{ such that:}$$

$$\mathbb{E}[v_2(x, z, t, \epsilon_2)|x, t] = \int_{\widetilde{z}} \sigma \log \left(e^{P(y=S|x,\widetilde{z})/\sigma} + e^{P(y_2^*=S|t)/\sigma} \right) dF(\widetilde{z}|x)$$

Dynamic Parameterization

Dynamic Model

Round 1:

$$v_1(x,t,\epsilon_1) = \max_{d_1 \in \{T,R\}} u_1(x,t,d_1) + \epsilon_1(d_1), \text{ such that:}$$

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$$\mathbb{E}[v_2(x,z,t,\epsilon_2)|x,t] = \int_{\tilde{z}} \sigma \log \left(e^{P(y=S|x,\tilde{z})/\sigma} + e^{P(y_2^*=S|t)/\sigma} \right) dF(\tilde{z}|x)$$

Conditional Choice Probabilities:

$$P(d_r|x,(z),t) = \frac{\exp(u_r(x,(z),t,d_r)/\sigma)}{\sum_{\tilde{d}_r \in D_r} \exp(u_r(x,(z),t,\tilde{d}_r)/\sigma)}$$

Dynamic Parameterization

Static Model

- **Goal:** Make Round 1 cutoff a probability bounded between 0 and 1

▸▸ Static Parameterization

Static Model

- **Goal:** Make Round 1 cutoff a probability bounded between 0 and 1

Round 2:

$$v_2(x,z,t,\epsilon_2) = \max_{d_2 \in \{A,R\}} u_2(x,z,t,d_2) + \epsilon_2(d_2), \text{ such that:}$$

$$u_2(x,z,t,d_2) = \underbrace{P(y=S|x,z)\mathbb{1}(d_2=A)}_{\text{If accept, get } P(\text{Success})} + \underbrace{P(y_2^*=S|t)\mathbb{1}(d_2=R)}_{\text{If reject, get } P(\text{Cutoff})}$$

Static Parameterization

Static Model

- **Goal:** Make Round 1 cutoff a probability bounded between 0 and 1

Round 2:

$$v_2(x, z, t, \epsilon_2) = \max_{d_2 \in \{A,R\}} u_2(x, z, t, d_2) + \epsilon_2(d_2), \text{ such that:}$$

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Round 1:

$$v_1(x, t, \epsilon_1) = \max_{d_1 \in \{T,R\}} u_1(x, t, d_1) + \epsilon_1(d_1), \text{ such that:}$$

$$u_1(x, t, d_1) = \underbrace{P(y = S|x)\mathbb{1}(d_1 = T)}_{\text{If transition, get } P(\text{Success})} + \underbrace{P(y_1^* = S|t)\mathbb{1}(d_1 = R)}_{\text{If reject, get } P(\text{Cutoff})}$$

Static Parameterization

Static Model

- **Goal:** Make Round 1 cutoff a probability bounded between 0 and 1

Round 2:

$$v_2(x, z, t, \epsilon_2) = \max_{d_2 \in \{A,R\}} u_2(x, z, t, d_2) + \epsilon_2(d_2), \text{ such that:}$$

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- $P(y = S|x)$ estimates inconsistent, but fitted values account for x's effect on z

Static Parameterization

Portfolio Choice with Matriculation

- Accept subset of applicants with highest sum of success times matriculation probabilities subject to capacity constraint on expected number of matriculants

- For each applicant $n \in \{1, \ldots, N\}$, make decision $d_n \in \{\text{Accept}, \text{Reject}\}$ given:

$$\max_{(d_1,\ldots,d_N)\in\{A,R\}^N} \sum_{n=1}^{N} \underbrace{P(y_n = S|x_n, z_n)}_{\text{Success probability}} \underbrace{P(m_n = M|x_n, z_n)}_{\text{Matriculation probability}} \underbrace{\mathbb{1}(d_n = A)}_{\text{Acceptance}},$$

$$\text{such that: } \sum_{n=1}^{N} \underbrace{P(m_n = M|x_n, z_n)}_{\text{Matriculation probability}} \underbrace{\mathbb{1}(d_n = A)}_{\text{Acceptance}} \leq N_M,$$

where $(x, z) =$ variables, $y \in \{\text{Success}, \text{Failure}\}$, $m \in \{\text{Matriculate}, \text{Decline}\}$, $N =$ number of applicants, and $N_M =$ maximum number of matriculants

Portfolio Choice with Matriculation

- Accept subset of applicants with highest sum of success times matriculation probabilities subject to capacity constraint on expected number of matriculants

$$\max_{(d_1,\ldots,d_N)\in\{A,R\}^N} \sum_{n=1}^{N} \underbrace{P(y_n = S|x_n, z_n)}_{\text{Success probability}} \underbrace{P(m_n = M|x_n, z_n)}_{\text{Matriculation probability}} \underbrace{\mathbb{1}(d_n = A)}_{\text{Acceptance}},$$

$$\text{such that: } \sum_{n=1}^{N} \underbrace{P(m_n = M|x_n, z_n)}_{\text{Matriculation probability}} \underbrace{\mathbb{1}(d_n = A)}_{\text{Acceptance}} \leq N_M$$

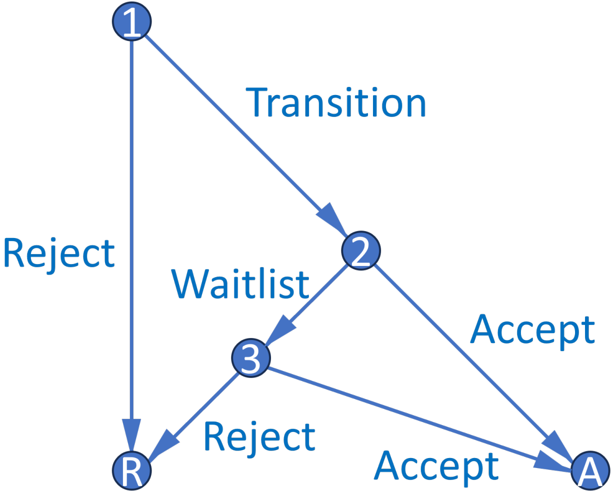
Theorem 1 (Proof)

For large N, this problem reduces to a cutoff rule problem on **success** *probabilities.*

- Likely matriculants more valuable, but also more expensive $\Rightarrow$ effects cancel
- **Upshot:** Matriculation probabilities only matter if there are dynamic effects

Cutoff Rule with Matriculation

Waitlist Model



- Three-round model features waitlist and accounts for applicants' decisions
- Equations analogous to those in baseline two-round dynamic model
- Dynamic mechanism incentivizes giving early acceptances to likely matriculants

Waitlist Equations

Waitlist Memory

- Respecify Round 3 cutoff $P(y_3^* = S|t)$, where t = year, as $P(y_3^* = S|\overline{m_{2A}})$
  - $\overline{m_{2A}}$ = average early accepted applicant's matriculation probability based on (x, z)
  - Enthusiasm variables can affect matriculation independently of success
  - $P(y_3^* = S|\overline{m_{2A}})$ increases in $\overline{m_{2A}}$ because larger $\overline{m_{2A}}$ means fewer openings
- What information available at start of Round 2 determines $\overline{m_{2A}}$?
  - For all transitioned applicants, $\ddot{m}_2$. $\ddot{m}_2$ is defined as $\overline{m_2}^t$ with m_2 excluded, where m_2 = applicant's own matriculation probability. Within t, low m_2 implies high $\ddot{m}_2$
  - Estimate $f_{\overline{m_{2A}}|\ddot{m}_2}$ on all transitioned applicants; slope parameter's expected sign is positive provided there is variation in $\overline{m_2}^t$ across years (e.g. due to Covid)

Waitlist Model Waitlist Notes

Waitlist Dynamics

Theorem 2 (Proof)

Success probability equal, an applicant's Round 2 acceptance probability is strictly increasing in their matriculation probability.

- Compared to high m_2 applicant, low m_2 applicant has high $\ddot{m}_2$, and therefore high $\overline{F}_{\overline{m_{2A}}|\ddot{m}_2}$, $\mathbb{E}[P(\text{Cutoff})_3]$, and $\mathbb{E}[v_3]$. This increases relative payoff of waitlisting them
- $\mathbb{E}[v_3]$ discounted so payoff from acceptance in Round 3 less than in Round 2
  - Captures chance of losing applicant to another university between rounds
  - If committee is more selective in Round 2, discount factor is closer to 1

★ **Upshot:** Accepting applicants who want to matriculate benefits the program

Waitlist Model Waitlist Notes

Outline

Maximum Likelihood Estimation

$$\mathcal{L}_N^U(\theta) = \prod_{n=1}^{N_T} \underbrace{f(z_n|x_n;\theta_F)}_{\text{Density of } z|x} \underbrace{P_{d_{1,n}}(\theta_T) P_{d_{2,n}}(\theta_A)^{\mathbb{1}(d_{2,n}=A)} (1 - P_{d_{2,n}}(\theta_A))^{\mathbb{1}(d_{2,n}=R)}}_{\text{Conditional choice probabilities}}$$

$$\underbrace{P_{y_n}(\theta_S)^{\mathbb{1}(y_n=S)} (1 - P_{y_n}(\theta_S))^{\mathbb{1}(y_n=F)}}_{\text{Outcome probabilities}} \prod_{n=N_T+1}^{N} \underbrace{f(z_n|x_n;\theta_F)}_{\text{Density of } z|x} \underbrace{(1 - P_{d_{1,n}}(\theta_T))}_{\text{Conditional choice probability}}$$

- In unrestricted likelihood $\mathcal{L}^U$, parameterize CCPs with flexible logit specifications
- In restricted likelihood $\mathcal{L}^R$, use model CCPs, which depend on structural parameters
- Do success probabilities implied by outcomes align with those implied by CCPs?

Static Likelihood Waitlist Likelihood

Cutoff Probability Identification

Theorem 3 (Proof)

The maximum likelihood cutoff probability estimate is such that the number of acceptances N_A equals the expected N_A. Also, for any cutoff probability and N_A, the likelihood is highest when the committee accepts the best N_A applicants.

- Identify each year's cutoffs by how selective committee is that year
- While selectivity identifies cutoffs, sorting improves restricted likelihood
  - If committee engages in sorting, likelihood-ratio test less likely to reject
  - $\mathrm{LR} = 2\big[\log(\hat{\mathcal{L}}^U) - \log(\hat{\mathcal{L}}^R)\big] \sim \chi^2_Q$, such that $Q = \dim(\theta^U) - \dim(\theta^R)$

Empirical Considerations

Unrestricted Dynamic AMEs (Optimal)

	Advanced Math	Committee Score	Transition	Accept	Success
GRE Quantitative Percentile	0.0160***	0.0581***	0.0209***	0.0173***	0.0183***
	(0.0020)	(0.0088)	(0.0019)	(0.0033)	(0.0039)
Gender	-0.0087	0.3312***	0.0002	0.0361	-0.0089
	(0.0308)	(0.1204)	(0.0298)	(0.0448)	(0.0481)
Demographic 1	0.1173***	-1.2807***	-0.0739*	-0.0853	-0.0651
	(0.0400)	(0.1529)	(0.0416)	(0.0659)	(0.0707)
Demographic 2	-0.0097	-0.9447***	0.0091	-0.0316	0.1110
	(0.0452)	(0.1759)	(0.0447)	(0.0691)	(0.0676)
Advanced Math		0.8894***		0.1340***	0.1217**
		(0.1239)		(0.0463)	(0.0512)
Committee Score				0.0167	0.0047
				(0.0113)	(0.0119)
Year Transition More			0.1727***	-0.2328***	
			(0.0276)	(0.0379)	

- Data simulated from reduced-form-calibrated data-generating parameters
- Committee's decision rule aligns with maximizing success probabilities

▸▸ Summary Statistics (Optimal) ▸▸ Full Unrestricted Dynamic Estimates (Optimal) ▸▸ Unrestricted Static Estimates (Optimal)

Unrestricted Dynamic AMEs (Suboptimal)

	Advanced Math	Committee Score	Transition	Accept	Success
GRE Quantitative Percentile	0.0160***	0.0581***	0.0194***	0.0074**	0.0175***
	(0.0020)	(0.0088)	(0.0020)	(0.0036)	(0.0039)
Gender	-0.0086	0.3310***	0.0377	0.0682	-0.0097
	(0.0308)	(0.1204)	(0.0297)	(0.0441)	(0.0475)
Demographic 1	0.1174***	-1.2830***	-0.1024**	-0.1053*	-0.0517
	(0.0400)	(0.1529)	(0.0412)	(0.0638)	(0.0700)
Demographic 2	-0.0094	-0.9475***	0.0066	-0.0167	0.1142*
	(0.0452)	(0.1759)	(0.0441)	(0.0675)	(0.0659)
Advanced Math		0.8895***		0.0800*	0.1360***
		(0.1239)		(0.0482)	(0.0504)
Committee Score				0.0422***	0.0010
				(0.0120)	(0.0121)
Year Transition More			0.1887***	-0.2301***	
			(0.0273)	(0.0398)	

- Data simulated from reduced-form-calibrated data-generating parameters
- *Demographic 1* and *Advanced Math* undervalued, *Committee Score* overvalued

Summary Statistics (Suboptimal) | Full Unrestricted Dynamic Estimates (Suboptimal) | Unrestricted Static Estimates (Suboptimal)

Restricted Static Estimates (Optimal)

	$P(\text{Cutoff})_1$	$P(\text{Cutoff})_2$	Success 1	Success 2	Sigma
Year Transition Fewer | Intercept	49.77%	36.60%	-10.0587***	-8.9338***	
	(38.43%, 61.13%)	(28.53%, 45.50%)	(2.2082)	(2.4363)	
GRE Quantitative Percentile			0.1090***	0.0882***	
			(0.0259)	(0.0275)	
Gender			0.0070	0.0220	
			(0.1080)	(0.1620)	
Demographic 1			-0.3346*	-0.2945	
			(0.1803)	(0.2626)	
Demographic 2			0.1444	0.2881	
			(0.1702)	(0.2608)	
Advanced Math				0.6055***	
				(0.1854)	
Committee Score				0.0657	
				(0.0419)	
Year Transition More	31.86%	64.56%			
	(27.27%, 36.83%)	(47.28%, 78.72%)			
Sigma					0.2149***
					(0.0597)
LR Statistic | DF | P-Value	8.4729	9	0.4873		

- Likelihood-ratio test does not reject model fitting the data
- In *Year Transition Fewer*, Round 1 cutoff probability > Round 2 cutoff probability

Full Restricted Static Estimates (Optimal)
Restricted Dynamic Estimates (Optimal)

Restricted Static Estimates (Suboptimal)

	$P(\text{Cutoff})_1$	$P(\text{Cutoff})_2$	Success 1	Success 2	Sigma
Year Transition Fewer | Intercept	53.84%	37.04%	-10.3327***	-7.2584***	
	(40.49%, 66.66%)	(27.83%, 47.29%)	(1.9333)	(2.2514)	
GRE Quantitative Percentile			0.1123***	0.0663**	
			(0.0227)	(0.0260)	
Gender			0.1010	0.0839	
			(0.1144)	(0.1650)	
Demographic 1			-0.4233**	-0.3725	
			(0.1783)	(0.2547)	
Demographic 2			0.1588	0.2935	
			(0.1773)	(0.2525)	
Advanced Math				0.5525***	
				(0.1957)	
Committee Score				0.1161***	
				(0.0447)	
Year Transition More	31.62%	66.37%			
	(26.62%, 37.07%)	(47.08%, 81.40%)			
Sigma					0.2473***
					(0.0680)
LR Statistic | DF | P-Value	19.2965	9	0.0228		

- Likelihood-ratio test rejects model fitting the data at 5% level
- In *Year Transition Fewer*, Round 1 cutoff probability > Round 2 cutoff probability

Full Restricted Static Estimates (Suboptimal) Restricted Dynamic Estimates (Suboptimal)

Unrestricted Waitlist AMEs (Optimal)

	Advanced Math	Committee Score	$\ddot{m}_2$	$\overline{m_{2A}}$	Transition	Accept 2	Accept 3	Success
GRE Quantitative Percentile	0.0164***	0.0564***	-0.0083*		0.0173***	0.0045	0.0082**	0.0204***
	(0.0020)	(0.0088)	(0.0045)		(0.0020)	(0.0028)	(0.0034)	(0.0035)
Gender	-0.0078	0.3118***	-0.0469		0.0116	-0.0503	-0.0223	-0.0082
	(0.0308)	(0.1188)	(0.0637)		(0.0296)	(0.0362)	(0.0404)	(0.0486)
Demographic 1	0.1376***	-1.5764***	0.0091		-0.0588	0.0284	0.0541	-0.0984
	(0.0401)	(0.1549)	(0.0902)		(0.0407)	(0.0600)	(0.0654)	(0.0716)
Demographic 2	0.0142	-1.3590***	0.0816		-0.0164	0.0493	0.0186	0.1001
	(0.0457)	(0.1784)	(0.0969)		(0.0449)	(0.0592)	(0.0675)	(0.0743)
Advanced Math		0.9127***	0.1322**			0.0303	-0.0076	-0.0256
		(0.1212)	(0.0669)			(0.0367)	(0.0484)	(0.0520)
Committee Score			0.0112			-0.0020	0.0086	0.0291**
			(0.0166)			(0.0096)	(0.0118)	(0.0133)
Year Transition/Matriculate More					0.1666***			
					(0.0277)			
$\ddot{m}_2$				1.4277***		-0.0182		
				(0.0007)		(0.0158)		
$\overline{m_{2A}}$							-0.1459***	
							(0.0034)	

- AME signs as expected $\Rightarrow$ results extend to three-round waitlist model

Full Unrestricted Waitlist Estimates (Optimal) Waitlist Summary Statistics (Optimal) Restricted Waitlist Estimates (Optimal)

Unrestricted Waitlist AMEs (Suboptimal)

	Advanced Math	Committee Score	$\ddot{m}_2$	$\overline{m_{2A}}$	Transition	Accept 2	Accept 3	Success
GRE Quantitative Percentile	0.0160***	0.0566***	-0.0082*		0.0218***	-0.0023	0.0062*	0.0178***
	(0.0020)	(0.0088)	(0.0045)		(0.0019)	(0.0032)	(0.0034)	(0.0040)
Gender	-0.0090	0.3124***	-0.0468		0.0684**	0.0499	-0.0954**	-0.0039
	(0.0308)	(0.1188)	(0.0637)		(0.0286)	(0.0386)	(0.0442)	(0.0505)
Demographic 1	0.1369***	-1.5750***	0.0087		-0.0387	-0.0205	-0.1554**	-0.0159
	(0.0401)	(0.1549)	(0.0902)		(0.0401)	(0.0592)	(0.0706)	(0.0801)
Demographic 2	0.0116	-1.3568***	0.0814		0.0901**	0.0359	-0.1432**	-0.0333
	(0.0457)	(0.1784)	(0.0969)		(0.0431)	(0.0606)	(0.0661)	(0.0811)
Advanced Math		0.9118***	0.1320**			0.0613	-0.0034	0.0268
		(0.1212)	(0.0669)			(0.0415)	(0.0470)	(0.0543)
Committee Score			0.0112			0.0007	0.0161	0.0074
			(0.0166)			(0.0087)	(0.0103)	(0.0122)
Year Transition/Matriculate More					0.1977***			
					(0.0264)			
$\ddot{m}_2$				1.0524***		-0.0414**		
				(0.0003)		(0.0192)		
$\overline{m_{2A}}$							-0.1962***	
							(0.0081)	

- AME signs as expected $\Rightarrow$ results extend to three-round waitlist model

Full Unrestricted Waitlist Estimates (Suboptimal) | Waitlist Summary Statistics (Suboptimal) | Restricted Waitlist Estimates (Suboptimal)

Outline

Likelihood-Ratio and Deviation Gains Tests

- **Likelihood-Ratio:** Determines whether model fits data generated by committee's decision rule, but not whether committee can do better by changing decision rule

- **Deviation Gains:** Suppose committee adopts model's decision rule. Will average success probability of acceptance/matriculation set increase, and if so, by how much?
  - Solve model with $\sigma = 0$ in CCPs, compute average yearly $P(\text{Success})$ of model's acceptance/matriculation set, and compare to that of actual decision rule's set
  - $\hat{\theta}_S^R$ may be biased to rationalize suboptimal behavior, so plug in $\hat{\theta}_S^U$
  - **Example:** If committee puts too little weight on *Advanced Math*, then its restricted success probability parameter estimate will be biased down

Optimality Tests Notes

Deviation Gains Interpretation

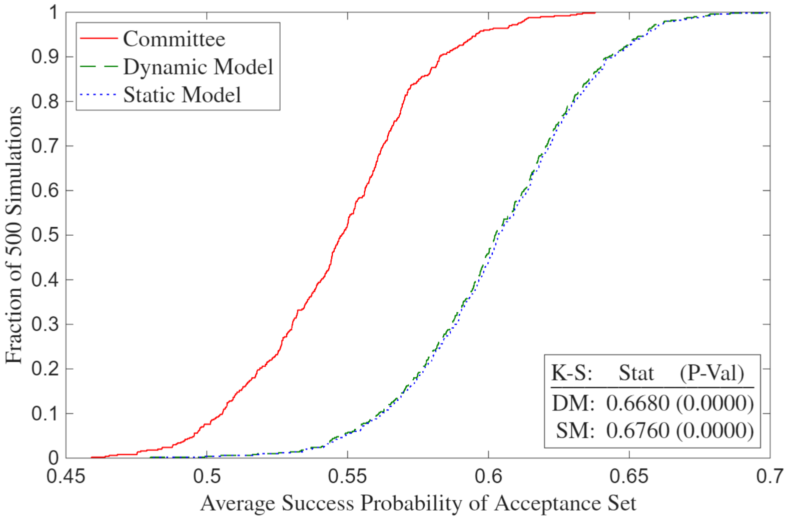
- Suppose there are meaningfully large deviation gains. Then committee may have incorrect beliefs about which types of applicants are most likely to succeed
  - Matriculation rate of model's acceptance set may be less than that of actual decision rule's acceptance set, making estimated gains an upper bound
  - In waitlist counterfactual, compare success probabilities of matriculation sets by simulating accepted applicants' matriculation decisions after Rounds 2 and 3

★ **Robustness:** Given too few observations for holdout set and infeasibility of large k-fold cross-validation due to runtime, implement randomization test

  - Compute average success probabilities with perturbations of $\hat{\theta}_S^U$

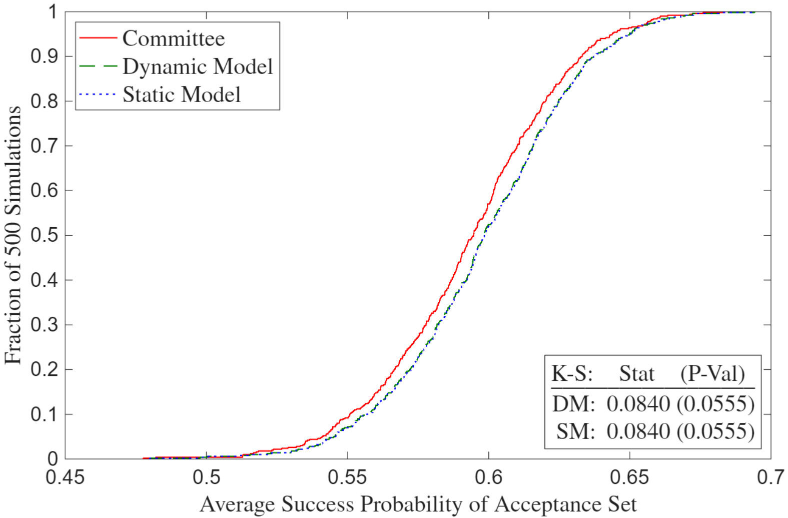
Deviation Gains Test

Deviation Gains (Suboptimal)



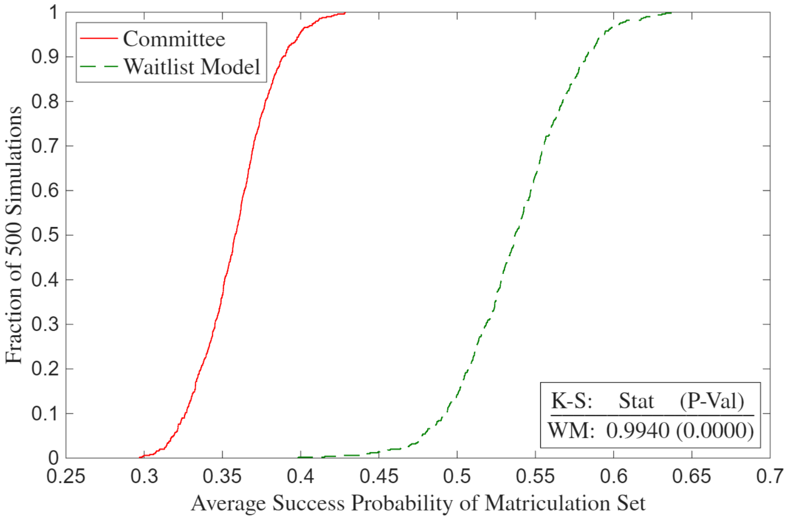
Full Deviation Gains (Suboptimal) Deviation Gains Missing (Suboptimal)

Deviation Gains (Optimal)



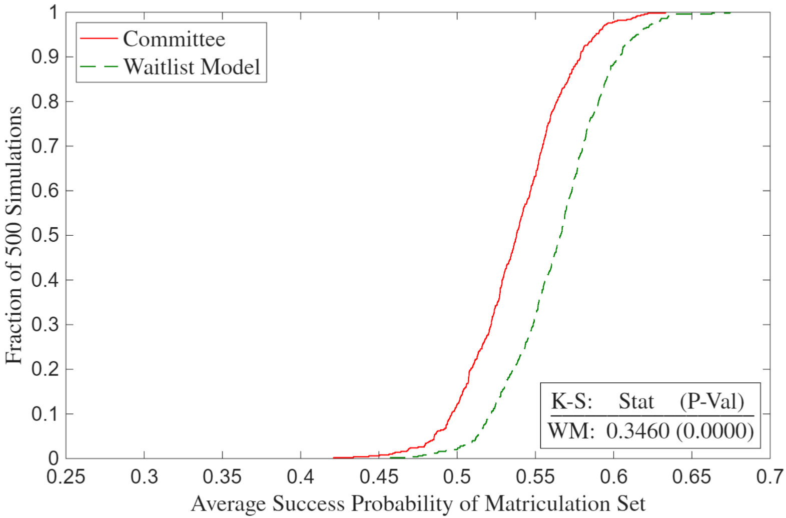
Full Deviation Gains (Optimal) Deviation Gains Missing (Optimal)

Waitlist Deviation Gains (Suboptimal)



Full Waitlist Deviation Gains (Suboptimal)
Waitlist Deviation Gains Missing (Suboptimal)

Waitlist Deviation Gains (Optimal)



Full Waitlist Deviation Gains (Optimal)   Waitlist Deviation Gains Missing (Optimal)

Conclusion

- **Economic Problem:** Selecting best options under costly evaluation
- **Application:** Graduate admissions using synthetic data protocol to protect privacy
- **Contribution:** Build models to test optimality and quantify deviation gains
  1. Economics admissions more data-driven than other social science programs
  2. Tradeoff between marginal cost of reading file vs. quality of marginal acceptance
     - Exploit tradeoff to calculate, in dollars, how much success is worth to committee
     - Alternatively, what if committee uses AI to transition all the applicants?
- **Future Research:** Two-sided matching model across multiple universities

Summary of Results | Multiyear Models

Thank You!

A1: Synthetic Rows $\neq$ Real Subjects

Transition	Accept	Success	GREQuantPct	Gender	Demographic1	Demographic2	AdvMath	ComScore
0	0	0	89	0	0	0	.	.
1	0	1	96	0	1	0	1	5
0	0	1	88	0	1	0	.	.
0	0	0	80	1	1	0	.	.
1	1	1	99	0	1	0	1	9
1	0	1	81	0	0	1	1	4
1	0	1	92	0	1	0	1	4
1	1	1	93	0	0	1	0	6
1	0	1	83	1	0	1	0	7
0	0	0	87	0	1	0	.	.

$$\Downarrow$$

Transition	Accept	Success	GREQuantPct	Gender	Demographic1	Demographic2	AdvMath	ComScore
1	0	0	90	1	1	0	0	5
1	0	0	83	0	0	1	1	6
1	1	1	91	0	0	1	0	5
1	1	1	92	0	0	1	0	5
0	0	1	83	0	0	0	.	.
1	0	0	93	0	0	1	0	9
0	0	0	84	0	0	1	.	.
1	1	1	88	0	1	0	1	4
1	0	1	86	0	1	0	0	6
0	0	1	86	1	0	1	.	.

Synthetic Data Protocol

A1: Dependent Variables

Table 1a: Dependent Variables

Admission	Success
$\mathbb{1}$(Transition)	**$\mathbb{1}$(Complete PhD Program)**
$\mathbb{1}$(Accept)	**$\mathbb{1}$(Academic Placement)**
$\mathbb{1}$(Waitlist)	**$\mathbb{1}$(Government Placement)**
$\mathbb{1}$(Open House)	**$\mathbb{1}$(Consulting Placement)**
$\mathbb{1}$(Matriculate)	**$\mathbb{1}$(Tech Placement)**
$\mathbb{1}$(Attend PhD Program)	**Placement U.S. Ranking**
PhD Program U.S. Ranking	**Placement Global Ranking**
PhD Program Global Ranking	**$\mathbb{1}$(Good Placement)**

- Economics-only variables bold, non-economics-only variables italic
- U.S. News PhD program rankings, IDEAS/RePEc placement rankings
  - For non-tenure track, use weighted average of university's and maximum rankings
  - For non-academia, use average of ChatGPT, Claude, and Gemini's rankings

Data Description

A1: Objective Variables

Table 1b: Objective Independent Variables

Demographic	Performance	Economics-Only Performance
$\mathbb{1}$(Covid Year)	GRE Verbal Percentile	**Masters GPA**
Winsorized Age	GRE Quantitative Percentile	**$\mathbb{1}$(Missing Masters GPA)**
$\mathbb{1}$(Female)	GRE Analytic Percentile	**$\mathbb{1}$(Elite U.S. Masters)**
$\mathbb{1}$(U.S. African/Hispanic/Native)	$\mathbb{1}$(Missing GRE Percentiles)	**$\mathbb{1}$(Elite International Masters)**
$\mathbb{1}$(U.S. Asian)	Undergraduate GPA	**$\mathbb{1}$(Other International Masters)**
$\mathbb{1}$(International Asian)	$\mathbb{1}$(Missing Undergraduate GPA)	**$\mathbb{1}$(Research Experience)**
$\mathbb{1}$(International Other)	TOEFL/IELTS Score	**Objective Score**
	$\mathbb{1}$(Missing TOEFL/IELTS Score)	**Relative Committee Score**
	$\mathbb{1}$(Elite U.S. University)	
	$\mathbb{1}$(Elite U.S. Liberal Arts College)	
	$\mathbb{1}$(Elite International University)	
	$\mathbb{1}$(Other International University)	
	$\mathbb{1}$(Graduate Degree)	
	$\mathbb{1}$(Work Experience)	
	Number of Professor Recommenders	
	Number of Prolific Recommenders	
	Concentration Dummy Variables	

Data Description

A1: Subjective Variables

Table 1c: Subjective Independent Variables

Recommendation Letter	Essay/CV/Supplemental Form
Relative Letter Length	**Essay Length (Essay)**
Relative Letter Features	**$\mathbb{1}$(Specific Topic) (Essay)**
Positive Words (YS 2012)	**$\mathbb{1}$(Specific Professor) (Essay)**
Negative Words (YS 2012)	**$\mathbb{1}$(Economics Work Experience) (CV)**
Standout Words (BEMS 2022)	**$\mathbb{1}$(Working Paper) (CV)**
Ability Words (BEMS 2022)	**$\mathbb{1}$(Publication) (CV)**
Research Words (BEMS 2022)	**$\mathbb{1}$(Coding) (CV)**
Grindstone Words (BEMS 2022)	**Number of Math Courses (Supplemental)**
Teaching Words (BEMS 2022)	**$\mathbb{1}$(Advanced Math) (Supplemental)**
Communal Words (BEMS 2022)	**$\mathbb{1}$(Theory Field) (Essay/CV)**
Agentic Words (MHM 2009)	**$\mathbb{1}$(Applied Field) (Essay/CV)**

- Dictionaries from Madera, Hebl & Martin (2009), Young & Soroka (2012), and Bai, Esche, MacLeod & Shi (2022)
- #MathCourses and $\mathbb{1}$(AdvMath) objective after 2020

Data Description

A1: Academia-Equivalent Rankings (Government)

- **European Institutions:** European Central Bank (40), HM Treasury (93)
- **Foreign Central Banks:** Banco Central do Brasil (93), Banco de México (93), Bank of Canada (80), Bank of England (67), Bank of Israel (80), Bank of Italy (93), Bank of Japan (80), Bank of Spain (93), Banque de France (93), Central Bank of Chile (93), Central Bank of Colombia (98), Central Bank of Korea (93), Central Bank of Turkey (98), Norges Bank (80), Reserve Bank of Australia (80), Reserve Bank of India (93), Reserve Bank of New Zealand (80), Sveriges Riksbank (80), Swiss National Bank (80)
- **Multilaterals/International:** African Development Bank (93), Asian Development Bank (93), Bank for International Settlements (53), European Bank for Reconstruction and Development (93), European Investment Bank (93), Inter-American Development Bank (80), International Monetary Fund (40), Statistics Canada (93), World Bank (40)
- **Policy Research Institutes:** American Enterprise Institute (93), American Institutes for Research (107), Becker Friedman Institute (80), Brookings Institution (80), Center for Global Development (80), Center for Migration Studies in New York (112), Center for Strategic and International Studies (112), Cowles Foundation (80), Harris School Policy Labs (93), Hoover Institution (93), IDinsight (107), Innovations for Poverty Action (93), J-PAL (80), MDRC (107), National Bureau of Economic Research (80), Peterson Institute for International Economics (80), Pew Research Center (107), RAND Corporation (80), Resources for the Future (93), Urban Institute (107)
- **U.S. Executive/Cabinet:** Department of Commerce (107), Department of Justice (80), Department of Labor (107), Department of the Treasury (80)
- **U.S. Executive Policy Offices:** Council of Economic Advisers (80), Office of Management and Budget (93)
- **U.S. Federal Reserve System:** Board of Governors (40), Atlanta (93), Boston (93), Chicago (80), Cleveland (93), Dallas (93), Kansas City (93), Minneapolis (80), New York (67), Philadelphia (80), Richmond (93), San Francisco (80), St. Louis (80)
- **U.S. GSE/Housing Finance:** Fannie Mae (120), Freddie Mac (120)
- **U.S. Independent Agencies:** Commodity Futures Trading Commission (93), Federal Deposit Insurance Corporation (93), Federal Energy Regulatory Commission (93), Federal Housing Finance Agency (93), Federal Trade Commission (80), Office of Financial Research (80), Securities and Exchange Commission (93)
- **U.S. Legislative Committees:** Congressional Budget Office (80), Congressional Research Service (107), Joint Committee on Taxation (80), Joint Economic Committee (107)
- **U.S. Science and Research:** National Science Foundation (107)
- **U.S. Statistical Agencies:** Bureau of Economic Analysis (80), Bureau of Labor Statistics (80), Census Bureau (80)

Data Description

A1: Academia-Equivalent Rankings (Consulting/Tech/Other)

- **Consulting:** Aecon Consulting (130), AlixPartners (130), Analysis Group (120), Bain & Compnay (120), Bates White (120), Berkeley Research Group (120), Boston Consulting Group (120), Brattle Group (120), Charles River Associates (120), Coleman Research (130), Compass Lexecon (120), Cornerstone Research (120), Deloitte Economic and Financial Advisory (125), Econic Partners (130), Economists Incorporated (120), Edgeworth Economics (120), Ernst & Young Economic Advisory (125), Frontier Economics (120), FTI Consulting (120), Guidehouse (130), KPMG Economics & Valuation (125), Matrix Economics (130), McKinsey & Company (120), Mercer (135), NERA Economic Consulting (120), Oliver Wyman (120), PwC Economics, Roland Berger (130), Willis Towers Watson (135)
- **Tech (Athey & Luca 2019):** Airbnb (107), Alibaba (120), Amazon (93), AppNexus (135), Apple (93), Block/Square (120), ByteDance/TikTok (120), CoreLogic (130), Coursera (120), DStillery (135), Didichuxing (130), Digonex (130), DoorDash (120), eBay (120), ECONorthwest (125), Expedia (120), Forkcast (135), Glassdoor (120), Google (93), Granular (135), Groupon (130), Houzz (130), Huawei (120), IBM (120), Indeed (120), ING (130), Instacart (120), Intel (120), Kensho (125), Lending Club (135), LinkedIn (107), Lyft (120), Meta/Facebook (93), Microsoft (93), Netflix (93), Nuna (135), Nvidia (120), Pandora (135), PayPal (120), Pinterest (120), Prattle (135), Quantco (130), Quora (130), Redfin (120), Ripple (135), Roblox (120), Rover (135), Salesforce (120), Shopify (120), Spotify (120), Stripe (120), Trulia (130), Uber (107), Upwork (135), Visa (112), Walmart (125), Wealthfront (130), Yahoo (125), Yelp (130), Zillow (107)
- **Tech Labs:** Amazon Science (53), Apple Machine Learning Research (80), DeepMind (67), Google Research (40), Meta Research (80), Microsoft Research (40), Netflix Research (93), OpenAI Research (80), Uber Research (93)
- **Other:** AIG (135), Bank of America, (125), Bloomberg (125), Boeing (135) Capital One (125), Exelon (135), ExxonMobil (130), Ford (135), General Electric (135), General Motors (135), Goldman Sachs (125), JPMorgan Chase (125), Liberty Mutual (135), Moody's Analytics (125), Morningstar (125), Nielsen (135), PNC (130), Progressive (135), S&P Global (125), Shell (130), Swiss Re (125), Toyota (130), Other (135), No Placement (150)

Data Description

A1: Dictionaries

- **Recommendation Letters:** Porter stemmer reduces words to their roots
  - **Positive/Negative Words:** Young & Soroka (2012)'s Lexicoder Sentiment Dictionary
  - **Standout, Ability, Research, Grindstone, Communal Words:** Bai, Esche, MacLeod & Shi (2022)
  - **Agentic Words:** assertive, confident, aggressive, ambitious, dominant, forceful, independent, daring, outspoken, intellectual (Madera, Hebl & Martin 2009); **AND** audacious, bold, command, compete, decisive, determine, drive, enterprise, fearless, influential, leader, pioneer, powerful, proactive, resilient, resourceful, self-assured, strategic, tenacious, vision
  - **Teaching Words:** academic, assess, clarity, coach, collaborate, communicate, cultivate, curriculum, demonstrate, develop, educate, encourage, engage, enlighten, evaluate, explain, facilitate, foster, guide, impart, inspire, insight, instruct, knowledge, learn, lesson, mentor, nurture, participate, pedagogy, present, scholar, support, teach, train, tutor, workshop
- **Essays and CVs:**
  - **Specific Topic:** applied, asset, behavior, climate, computation, data, development, dynamic programming, economics, education, empirical, environment, experiment, finance, fiscal, game theory, health, immigration, industrial, inequality, international, io, labor, linear programming, macro, math, metrics, micro, monetary, policy, political, poverty, pricing, probability, public, sports, statistic, theory, trade, urban
  - **Economics Work Experience:** assistant, fed, imf, international monetary fund, predoc, ra, research, treasury, world bank
  - **Working Paper:** arxiv, center for economic policy research, cepr, econpapers, national bureau of economic research, nber, research papers in economics, repec, social science research network, ssrn, working paper
  - **Publication:** Journal names from IDEAS/RePEc Aggregate Rankings for Journals
  - **Coding:** c/c++, eviews, fortran, java, jax, julia, latex, matlab, python, r, sas, stata, webscrape

Data Description

A1: Inference vs. Prediction

- Hard to obtain consistent estimates due to omitted variables
  - **Example:** Don't observe effort (e.g. hours worked). Can bias coefficients upward if predictors correlated with effort and success are independent of effort
  - Existing literature also suffers from this problem, though BEMS (2022) parse recommendation letters for "grindstone terms" (e.g. depend*, diligen*)
- Research questions emphasize prediction over inference
  - Mullainathan & Spiess (2017) distinguish $\hat{\beta}$ vs. $\hat{y}$ problems
  - If GRE predicts success, committee should use it regardless of why
  - See Reduced-Form Summary for prediction-based methods

Data Description

A1: Sample Selection

- Determinants of success conditional on applying vs. matriculating
- BEMS (2022) prove that if $P(\text{Success}|\text{Skill})$ is an S-curve, then $\hat{\beta}$ will be smaller for more selected samples. Consistent with empirical results
- If there aren't some types of outcomes data (e.g. grades, passing comps) for all applicants, or such data are too hard to obtain, use Heckman correction
    - Let $y_n^* = x_n\beta + u_n$, $d_n = \mathbb{1}(z_n\gamma + v_n > 0)$, and $y_n = d_n y_n^*$
    - **Step 1:** Run probit of d on z and compute inverse Mills $\hat{\lambda}_n = \frac{\phi(z_n\hat{\gamma})}{\Phi(z_n\hat{\gamma})}$
    - **Step 2:** Run OLS, probit, or ordered probit of y on $(x, \hat{\lambda})$ to get $\hat{\beta}$
    - **Instruments:** Enthusiasm score, average acceptance rate/quality

Data Description

A1: Insufficiency of Comparing AMEs

- Cannot test optimality by comparing AMEs across regressions. Suppose:
  - Math skills have large positive effect on success, coding skills smaller positive effect
  - 25% of applicants have both skills, 25% math only, 25% coding only, 25% neither
  - Committee can accept half of applicants, and other half attend different university
- Optimizing committee accepts half with math and ignores coding
  - **Acceptance Regression:** $\text{AME}_{\text{Math}} = 1$, $\text{AME}_{\text{Coding}} = 0$
  - **Success Regression:** $1 > \text{AME}_{\text{Math}} > \text{AME}_{\text{Coding}} > 0$
  - Despite optimality, acceptance and success AMEs not equal across regressions
- **Upshot:** Relationship between AMEs must be interpreted through a model

Acceptance vs. Success AMEs

A1: Wald Tests

- Test if admission and success AMEs are same across programs
  - **Example:** Does elite undergraduate university predict admission and/or success more or less for economics than for other programs?
  - **Data:** Simulated from reduced-form-calibrated data-generating parameters
- Can I test if acceptance AMEs equal success AMEs within programs?
  - Predictors of acceptance only (success only) may be overvalued (undervalued), provided committee wants to select based on a "success" model
  - **Problem:** Not a test if admissions decisions are optimal
  - Need structural model of admissions to conclude about optimality

Acceptance vs. Success AMEs

A1: Logit Wald Test Across Programs

Assume $\left(Y^E \perp\!\!\!\perp Y^{NE}\right)\middle|X$. Let $P\left(Y_n^E = 1\middle|x_n^E;\theta^E\right) = \frac{\exp(x_{n,0}^E\theta_0^E + x_{n,1}^E\theta_1^E)}{1+\exp(x_{n,0}^E\theta_0^E + x_{n,1}^E\theta_1^E)}$, and $P\left(Y_n^{NE} = 1\middle|x_n^{NE};\theta^{NE}\right) = \frac{\exp(x_{n,0}^{NE}\theta_0^{NE} + x_{n,1}^{NE}\theta_1^{NE})}{1+\exp(x_{n,0}^{NE}\theta_0^{NE} + x_{n,1}^{NE}\theta_1^{NE})}$. Finally, let $N = N_E + N_{NE}$. Then:

$$\mathcal{L}_N^U\left(y\middle|x;\theta\right) = \prod_{n=1}^{N_E} P\left(Y_n^E = 1\middle|x_n^E;\theta^E\right)^{Y_n^E}\left[1 - P\left(Y_n^E = 1\middle|x_n^E;\theta^E\right)\right]^{1-Y_n^E}$$

$$\prod_{n=1}^{N_{NE}} P\left(Y_n^{NE} = 1\middle|x_n^{NE};\theta^{NE}\right)^{Y_n^{NE}}\left[1 - P\left(Y_n^{NE} = 1\middle|x_n^{NE};\theta^{NE}\right)\right]^{1-Y_n^{NE}}.$$

- $Y \in \{\mathbb{1}(\text{Accept}), \mathbb{1}(\text{Attend Program}), \mathbb{1}(\text{Complete Program}), \mathbb{1}(\text{Good Placement})\}$
- **Test:** Let $g(\hat{\theta}) = \frac{1}{N_E}\sum_{n=1}^{N_E}\hat{P}_n^E(1-\hat{P}_n^E)\hat{\theta}_1^E - \frac{1}{N_{NE}}\sum_{n=1}^{N_{NE}}\hat{P}_n^{NE}(1-\hat{P}_n^{NE})\hat{\theta}_1^{NE}$. Then: $W = g(\hat{\theta})'[\nabla_\theta g(\hat{\theta})\hat{V}(\hat{\theta})\nabla_\theta g(\hat{\theta})']^{-1}g(\hat{\theta}) \sim \chi_Q^2$. Compare AMEs per Mood (2010)

Acceptance vs. Success AMEs

A1: Linear Wald Test Across Programs

Assume $\left(Y^E \perp\!\!\!\perp Y^{NE}\right)\big|X$, i.e. $\left(\text{Economics} \perp\!\!\!\perp \text{Non-Economics}\right)\big|\text{Predictors}$.

Let $f\left(y_n^E \big| x_n^E; \beta^E, \sigma_E^2\right) = \frac{1}{\sqrt{2\pi\sigma_E^2}} \exp\left[\frac{-1}{2\sigma_E^2}\left(y_n^E - x_{n,0}^E\beta_0^E - x_{n,1}^E\beta_1^E\right)^2\right]$, and

$f\left(y_n^{NE} \big| x_n^{NE}; \beta^{NE}, \sigma_S^2\right) = \frac{1}{\sqrt{2\pi\sigma_{NE}^2}} \exp\left[\frac{-1}{2\sigma_{NE}^2}\left(y_n^{NE} - x_{n,0}^{NE}\beta_0^{NE} - x_{n,1}^{NE}\beta_1^{NE}\right)^2\right]$. Then:

$$\mathcal{L}_N^U\left(y \big| x; \beta, \sigma^2\right) = \prod_{n=1}^{N_E} f\left(y_n^E \big| x_n^E; \beta^E, \sigma_E^2\right) \prod_{n=1}^{N_{NE}} f\left(y_n^{NE} \big| x_n^{NE}; \beta^{NE}, \sigma_{NE}^2\right).$$

- $Y \in \{\mathbb{1}(\text{Standardized Committee Score}), \mathbb{1}(\text{Standardized Placement Rank})\}$
- **Test:** Let $g(\hat{\beta}_1) = \hat{\beta}_1^E - \hat{\beta}_1^{NE}$. (Can also do likelihood-ratio test.)
  Then $W = g(\hat{\beta}_1)'[\nabla_{\beta,\sigma^2} g(\hat{\beta}_1)\hat{V}(\hat{\beta}, \hat{\sigma}^2)\nabla_{\beta,\sigma^2} g(\hat{\beta}_1)']^{-1} g(\hat{\beta}_1) \sim \chi_Q^2$
- **Assumption:** Homoskedasticity (i.e. $\forall n,\ \sigma_n^2 = \sigma^2$)

Acceptance vs. Success AMEs

A1: Additional Questions

- Are there different determinants of different types of success? (AKKLP 2007)
  - Need different skills at different stages in the program, such as grades vs. placement
  - For some programs, initial placement matters less than for economics
- Different determinants for international applicants? (KW 2000)
  - **Admission:** May have different preparation and/or interests
  - **Completion:** Depending on country, may have fewer outside options
  - **Placement:** May return to native country after graduation
- Different determinants over time? (2015 to 2023)
  - COVID-19 and other macro factors; changes in professions (e.g. more empirics)
  - For economics, increased importance of elite predocs and Fed RAships

Acceptance vs. Success AMEs

A2.1: Portfolio Choice to Cutoff Rule (BEMS 2022)

Portfolio Choice Problem:

$$\max_{(d_1,\ldots,d_N)\in\{A,R\}^N} \sum_{n=1}^{N} P(y_n = S|x_n, z_n)\mathbb{1}(d_n = A), \text{ such that: } \sum_{n=1}^{N} \mathbb{1}(d_n = A) \leq N_A$$

$$\mathcal{L}(d_1, \ldots, d_N; \lambda) = \sum_{n=1}^{N} \left[P(y_n = S|x_n, z_n) - \lambda\right]\mathbb{1}(d_n = A) + \lambda N_A$$

Cutoff Rule Solution:

$$\forall n \in \{1, \ldots, N\},\ d_n(x_n, z_n|\lambda^*) = \begin{cases} A & \text{if } P(y_n = S|x_n, z_n) > \lambda^* \\ \{A, R\} & \text{if } P(y_n = S|x_n, z_n) = \lambda^* \\ R & \text{if } P(y_n = S|x_n, z_n) < \lambda^* \end{cases}$$

Upshot: λ^* is cutoff probability. Denote it hereafter as $P(y^* = S)$

- $P(y^* = S) \in \left[P(y_{N_A+1} = S|x_{N_A+1}, z_{N_A+1}), P(y_{N_A} = S|x_{N_A}, z_{N_A})\right]$

Model Framework

A2.1: Models of Admissions

1. **Year-Static Model:** Committee ranks applicants based on objective variables, reads files of applicants above Cutoff 1, re-ranks surviving applicants based on all variables, and accepts surviving applicants above Cutoff 2

2. **Year-Dynamic Model:** Committee forms expectation in Round 1 about applicants who survive to Round 2. Favors applicants with objective variables positively correlated with good subjective variables

3. **Waitlist-Hybrid/Dynamic Models:** After Round 1, committee accepts or waitlists applicants in Round 2. After accepted applicants matriculate or don't matriculate, committee accepts or rejects waitlisted applicants in Round 3. Favors likely matriculants in Round 2 to increase selectivity in Round 3

Cutoff Rule Problem

A2.1: Description of Models

- **Round 2:** If accept applicant, get success probability $P(y = S|x, z)$, where Success $= \mathbb{1}(\text{Complete Program})$ or $\mathbb{1}(\text{Good Placement})$. If reject applicant, get $P(y_2^* = S|t) = P(\text{Success})$ of year t's marginal accepted applicant

- **Round 1:** If reject applicant, get $P(y_1^* = S|t) = P(\text{Success})$ of year t's marginal transitioned applicant. Can be less or greater than $P(y_2^* = S|t)$ depending on value placed on committee's time vs. admitting a successful cohort
  - **Year-Static:** If transition applicant, get $P(y = S|x)$, or $P(\text{Success})$ unconditional on z. It may differ from $P(y = S|x, z)$, though it still accounts for x's effect on z
  - **Year-Dynamic:** If transition applicant, get $\mathbb{E}[v_2(x, z, t, \epsilon_2)|x, t] =$ expected value of Round 2, where z is integrated out conditional on x via $F(z|x)$
  - **Year-Myopic:** In $\mathbb{E}[v_2(x, z, t, \epsilon_2)|x, t]$, replace $F(z|x)$ with $F(z)$

Cutoff Rule Problem

A2.1: Year-Static Parameterization

Unrestricted CCPs:

$$P_{d_1} = P\left(d_1 = T \middle| x, t; \theta_T\right) = \frac{\exp(f_T(x,t)\theta_T)}{1 + \exp(f_T(x,t)\theta_T)}$$

$$P_{d_2} = P\left(d_2 = A \middle| x, z, t; \theta_A\right) = \frac{\exp(f_A(x,z,t)\theta_A)}{1 + \exp(f_A(x,z,t)\theta_A)}$$

Success Probabilities:

$$P_{y_1} = P\left(y = S \middle| x; \theta_{S_1}\right) = \frac{\exp(f_{S_1}(x)\theta_{S_1})}{1 + \exp(f_{S_1}(x)\theta_{S_1})}$$

$$P_{y_2} = P\left(y = S \middle| x, z; \theta_{S_2}\right) = \frac{\exp(f_{S_2}(x,z)\theta_{S_2})}{1 + \exp(f_{S_2}(x,z)\theta_{S_2})}$$

Cutoff Probabilities:

$$P_{y_1^*} = P\left(y_1^* = S \middle| t; \theta_{S_1^*}\right) = \frac{\exp(f_{S_1^*}(t)\theta_{S_1^*})}{1 + \exp(f_{S_1^*}(t)\theta_{S_1^*})}$$

$$P_{y_2^*} = P\left(y_2^* = S \middle| t; \theta_{S_2^*}\right) = \frac{\exp(f_{S_2^*}(t)\theta_{S_2^*})}{1 + \exp(f_{S_2^*}(t)\theta_{S_2^*})}$$

Year-Static Model

A2.1: Year-Dynamic Parameterization

$$\mathbb{E}[v_2(x,z,t,\epsilon_2)|x,t] = \int_{\widetilde{z}} \sigma \log \left(\sum_{\widetilde{d}_2 \in \{A,R\}} e^{u_2(x,\widetilde{z},t,\widetilde{d}_2)/\sigma} \right) dF(\widetilde{z}|x)$$

$$= \int_{\widetilde{z}_1} \cdots \int_{\widetilde{z}_J} \Big[\cdot \Big] dF_1(\widetilde{z}_1|\widetilde{z}_2, \ldots \widetilde{z}_J, x) \cdots dF_J(\widetilde{z}_J|x)$$

- **Continuous:** $f_{z|x}(z_j|x;\beta_{F_{z|x,j}},\sigma^2_{F_{z|x,j}}) = \frac{1}{\sqrt{2\pi\sigma^2_{F_{z|x,j}}}} \exp\left[\frac{-1}{2\sigma^2_{F_{z|x,j}}}(z_j - g(x)\beta_{F_{z|x,j}})^2\right]$
- **Binary:** $P(z_j = 1|x;\theta_{F_{z|x,j}}) = \frac{\exp\left(g(x)\theta_{F_{z|x,j}}\right)}{1+\exp\left(g(x)\theta_{F_{z|x,j}}\right)}$
- **Multinomial:** $P(z_j = (k \neq K)|x;\theta_{F^k_{z|x,j}}) = \frac{\exp\left(g(x)\theta_{F^k_{z|x,j}}\right)}{1+\sum_{\ell=1}^{K-1}\exp\left(g(x)\theta_{F^\ell_{z|x,j}}\right)}$

Year-Dynamic Model

A2.1: Year-Static Likelihood

$$\mathcal{L}_N^U(\theta) = \prod_{n=1}^{N_T} P_{d_{1,n}}(\theta_T) P_{d_{2,n}}(\theta_A)^{\mathbb{1}(d_{2,n}=A)} (1 - P_{d_{2,n}}(\theta_A))^{\mathbb{1}(d_{2,n}=R)} \left[P_{y_{1,n}}(\theta_{S_1}) P_{y_{2,n}}(\theta_{S_2})\right]^{\mathbb{1}(y_n=S)}$$

$$\left[(1-P_{y_{1,n}}(\theta_{S_1}))(1-P_{y_{2,n}}(\theta_{S_2}))\right]^{\mathbb{1}(y_n=F)} \prod_{n=N_T+1}^{N} (1-P_{d_{1,n}}(\theta_T)) P_{y_{1,n}}(\theta_{S_1})^{\mathbb{1}(y_n=S)} (1-P_{y_{1,n}}(\theta_{S_1}))^{\mathbb{1}(y_n=F)}$$

- **Problem:** I don't observe success for recent years
  - **Solution:** Separate block for recent years without success subblocks
  - **Assumption:** Older years representative of recent years
- If years are similar, can make $(\theta_{S_1^*}, \theta_{S_2^*})$ in $\mathcal{L}^R$ intercept only

Maximum Likelihood Estimation

A2.1: Year-Dynamic Heckman-Corrected Likelihood

$$\mathcal{L}_N^U(\theta) = \prod_{n=1}^{N_T} \Phi(x_n, t_n; \theta_H) f(z_n | x_n, \frac{\phi(x_n, t_n; \theta_H)}{\Phi(x_n, t_n; \theta_H)}; \theta_F) P_{d_{1,n}}(\theta_T) P_{d_{2,n}}(\theta_A)^{\mathbb{1}(d_{2,n}=A)} (1 - P_{d_{2,n}}(\theta_A))^{\mathbb{1}(d_{2,n}=R)}$$
$$P_{y_n}(\theta_S)^{\mathbb{1}(y_n=S)} (1 - P_{y_n}(\theta_S))^{\mathbb{1}(y_n=F)} \prod_{n=N_T+1}^{N} (1 - \Phi(x_n, t_n; \theta_H))(1 - P_{d_{1,n}}(\theta_T))$$

- I may not observe z for applicants who didn't survive Round 1
- Estimate Heckman (1979)-corrected full-information likelihood
- **Heckman Instrument:** Year t affects d_1 but not z

⏩ Maximum Likelihood Estimation

A2.1: Conditional Independence Assumption

- Should I assume success is independent of admission conditional on predictors?
  - This university aside, if you don't get into anywhere good, you're unlikely to succeed
  - Can bias $\hat{\theta}_S$ upward since without loss of generality, a low GRE is correlated with not getting in anywhere good, which itself prevents you from succeeding
- So should I replace $P\left(y = S \middle| x; \theta_S\right)$ with $P\left(y = S \middle| d, x; \theta_S\right)$?
  - **Problem 1:** If I condition y on $d = \mathbb{1}(\text{Accept})$, I would be "logistically regressing" d on y on d in restricted likelihood, which will fail
  - **Problem 2:** Because d is a function of x, even conditioning y on x and $d = \mathbb{1}(\text{Attend Program})$ will "collapse" $\hat{\theta}_S$ (except for $\hat{\theta}_S^d$)
  - ★ **Example:** In AKKLP (2007), quantitative GRE predicts course grades but not when Committee Score is included; coefficient even goes negative for Metrics Grade
  - **Problem 3:** Committee doesn't know *ex-ante* whether d will be 1 or 0

⏩ Maximum Likelihood Estimation

A2.1: Empirical Considerations

- **Selection Effects:** Track success for all applicants, including non-matriculants
  - In selected samples, success parameters are biased down (e.g. quantitative GRE)
- **Potential Outcomes:** Track which graduate program all applicants attended, and add expected program ranking conditional on (x, z) as control function
  - If a variable only predicts success by helping applicant get into elite graduate program, then committee should not use that variable to rank applicants
- **Unobservables:** I may not observe all information that committee observes
  - **Example:** Recommendation letter has nuances that algorithms can't detect
  - Include subjective committee score in z as a proxy for this information

Cutoff Probability Identification

A2.1: Cutoff Rule with Matriculation

Portfolio Choice Problem:

$$\max_{\delta \in \{\delta | \delta : \mathbb{R}^K \to [0,1]\}} \int_{w \in \mathbb{R}^K} P(y = S|w) P(m = M|w) \delta(w) f(w) dw,$$

$$\text{such that: } \int_{w \in \mathbb{R}^K} P(m = M|w) \delta(w) f(w) dw \leq N_M$$

$$\mathcal{L}(\delta; \lambda) = \int_{w \in \mathbb{R}^K} \left[P(y = S|w) - \lambda \right] P(m = M|w) \delta(w) f(w) dw + \lambda N_M$$

Cutoff Rule Solution:

$$\forall w \in \mathbb{R}^K, \ \delta(w|\lambda^*) = \begin{cases} 1 & \text{if } P(y = S|w) > \lambda^* \\ [0,1] & \text{if } P(y = S|w) = \lambda^* \\ 0 & \text{if } P(y = S|w) < \lambda^* \end{cases}$$

Upshot: Point-identified cutoff probability λ^* is with respect to success probabilities

Portfolio Choice with Matriculation

A2.1: Waitlist Model 1

Round 3:

$$v_3(x, z, \overline{m_{2A}}, \epsilon_3) = \max_{d_3 \in \{A,R\}} u_3(x, z, \overline{m_{2A}}, d_3) + \epsilon_3(d_3), \text{ such that:}$$

$$u_3(x, z, \overline{m_{2A}}, d_3) = \underbrace{P(y = S|x, z)\mathbb{1}(d_3 = A)}_{\text{If accept, get } P(\text{Success})} + \underbrace{P(y_3^* = S|\overline{m_{2A}})\mathbb{1}(d_3 = R)}_{\text{If reject, get } P(\text{Cutoff})}$$

Round 2:

$$v_2(x, z, \ddot{m}_2, \epsilon_2) = \max_{d_2 \in \{A,W\}} u_2(x, z, \ddot{m}_2, d_2) + \epsilon_2(d_2), \text{ such that:}$$

$$u_2(x, z, \ddot{m}_2, d_2) = \underbrace{P(y = S|x, z)\mathbb{1}(d_2 = A)}_{\text{If accept, get } P(\text{Success})} + \underbrace{\beta\mathbb{E}[v_3(x, z, \overline{m_{2A}}, \epsilon_3)|x, z, \ddot{m}_2]\mathbb{1}(d_2 = W)}_{\text{If waitlist, get discounted } \mathbb{E}[\text{Social Surplus}]}, \text{such that:}$$

$$\mathbb{E}[v_3(x, z, \overline{m_{2A}}, \epsilon_3)|x, z, \ddot{m}_2] = \int_{\widetilde{\overline{m_{2A}}}} \sigma \log\left(\sum_{\tilde{d}_3 \in \{A,R\}} e^{u_3(x,z,\widetilde{\overline{m_{2A}}},\tilde{d}_3)/\sigma}\right) dF_{\overline{m_{2A}}|\ddot{m}_2}(\widetilde{\overline{m_{2A}}}|\ddot{m}_2)$$

Waitlist Decision Graph

A2.1: Waitlist Model 2

Round 1:

$$v_1(x,t,\epsilon_1) = \max_{d_1 \in \{T,R\}} u_1(x,t,d_1) + \epsilon_1(d_1), \text{ such that:}$$

$$u_1(x,t,d_1) = \underbrace{\mathbb{E}[v_2(x,z,\ddot{m}_2,\epsilon_2)|x]\mathbb{1}(d_1 = T)}_{\text{If transition, get } \mathbb{E}[\text{Social Surplus}]} + \underbrace{L(y_1^* = S|t)\mathbb{1}(d_1 = R)}_{\text{If reject, get } L(\text{Cutoff})}, \text{ such that:}$$

$$\mathbb{E}[v_2(x,z,\ddot{m}_2,\epsilon_2)|x] = \int_{\widetilde{z}} \int_{\widetilde{\ddot{m}_2}} \sigma \log \left(\sum_{\widetilde{d}_2 \in \{A,R\}} e^{u_2(x,\widetilde{z},\widetilde{\ddot{m}_2},\widetilde{d}_2)/\sigma} \right) dF_{\ddot{m}_2|x,z}(\widetilde{\ddot{m}_2}|x,\widetilde{z})dF_{z|x}(\widetilde{z}|x)$$

Conditional Choice Probabilities:

$$P(d_r|\text{states}) = \frac{\exp(u_r(\text{states}, d_r)/\sigma)}{\sum_{\widetilde{d}_r \in D_r} \exp(u_r(\text{states}, \widetilde{d}_r)/\sigma)}$$

Waitlist Decision Graph

A2.1: Waitlist Model 2

Round 1 (Hybrid):

$$v_1(x, t, \epsilon_1) = \max_{d_1 \in \{T,R\}} u_1(x, t, d_1) + \epsilon_1(d_1), \text{ such that:}$$

$$u_1(x, t, d_1) = \underbrace{P(y = S|x)\mathbb{1}(d_1 = T)}_{\text{If transition, get } P(\text{Success})} + \underbrace{P(y_1^* = S|t)\mathbb{1}(d_1 = R)}_{\text{If reject, get } P(\text{Cutoff})}$$

Conditional Choice Probabilities:

$$P(d_r|\text{states}) = \frac{\exp(u_r(\text{states}, d_r)/\sigma)}{\sum_{\widetilde{d}_r \in D_r} \exp(u_r(\text{states}, \widetilde{d}_r)/\sigma)}$$

Waitlist Decision Graph

A2.1: Waitlist-Dynamic Parameterization 1

Unrestricted CCPs:

$$P_{d_1} = P\left(d_1 = T \middle| x, t; \theta_T\right) = \frac{\exp(f_T(x,t)\theta_T)}{1 + \exp(f_T(x,t)\theta_T)}$$

$$P_{d_2} = P\left(d_2 = A \middle| x, z, \ddot{m}_2; \theta_{A_2}\right) = \frac{\exp(f_{A_2}(x,z,\ddot{m}_2)\theta_{A_2})}{1 + \exp(f_{A_2}(x,z,\ddot{m}_2)\theta_{A_2})}$$

$$P_{d_3} = P\left(d_3 = A \middle| x, z, \overline{m_{2A}}; \theta_{A_3}\right) = \frac{\exp(f_{A_3}(x,z,\overline{m_{2A}})\theta_{A_3})}{1 + \exp(f_{A_3}(x,z,\overline{m_{2A}})\theta_{A_3})}$$

Success Probability:

$$P_y = P\left(y = S \middle| x, z; \theta_S\right) = \frac{\exp(f_S(x,z)\theta_S)}{1 + \exp(f_S(x,z)\theta_S)}$$

Cutoff Level/Probability:

$$L_{y_1^*} = L\left(y_1^* = S \middle| t; \theta_{S_1^*}\right) = \exp(f_{S_1^*}(t)\theta_{S_1^*})$$

$$P_{y_3^*} = P\left(y_3^* = S \middle| \overline{m_{2A}}; \theta_{S_3^*}\right) = \frac{\exp(f_{S_3^*}(\overline{m_{2A}})\theta_{S_3^*})}{1 + \exp(f_{S_3^*}(\overline{m_{2A}})\theta_{S_3^*})}$$

Waitlist Decision Graph

A2.1: Waitlist-Dynamic Parameterization 2

★ Assume z and $\ddot{m}_2$ are conditionally independent:

$$\mathbb{E}[v_2(x,z,\ddot{m}_2,\epsilon_2)|x] = \int_{\widetilde{z}}\int_{\widetilde{\ddot{m}_2}} \sigma \log\left(\sum_{\widetilde{d}_2\in\{A,R\}} e^{u_2(x,\widetilde{z},\widetilde{\ddot{m}_2},\widetilde{d}_2)/\sigma}\right) dF_{\ddot{m}_2|x,z}(\widetilde{\ddot{m}_2}|x,\widetilde{z})dF_{z|x}(\widetilde{z}|x)$$

$$= \int_{\widetilde{z}_1}\cdots\int_{\widetilde{z_{J_z}}}\int_{\widetilde{\ddot{m}_2}}\Big[\cdot\Big] dF_{\ddot{m}_2|x,z}(\widetilde{\ddot{m}_2}|x,\widetilde{z})dF_{z|x,1}(\widetilde{z}_1|\widetilde{z}_2,\ldots,\widetilde{z_{J_z}},x)\cdots dF_{z|x,J_z}(\widetilde{z_{J_z}}|x)$$

$$\mathbb{E}[v_3(x,z,\overline{m_{2A}},\epsilon_3)|x,z,\ddot{m}_2] = \int_{\widetilde{\overline{m_{2A}}}} \sigma \log\left(\sum_{\widetilde{d}_3\in\{A,R\}} e^{u_3(x,z,\widetilde{\overline{m_{2A}}},\widetilde{d}_3)/\sigma}\right) dF_{\overline{m_{2A}}|\ddot{m}_2}(\widetilde{\overline{m_{2A}}}|\ddot{m}_2)$$

- **Continuous:** $f_{z|x}(z_j|x;\beta_{F_{z|x,j}},\sigma^2_{F_{z|x,j}}) = \frac{1}{\sqrt{2\pi\sigma^2_{F_{z|x,j}}}}\exp\left[\frac{-1}{2\sigma^2_{F_{z|x,j}}}(z_j - g(x)\beta_{F_{z|x,j}})^2\right]$
- **Binary:** $P(z_j = 1|x;\theta_{F_{z|x,j}}) = \frac{\exp\left(g(x)\theta_{F_{z|x,j}}\right)}{1+\exp\left(g(x)\theta_{F_{z|x,j}}\right)}$
- **Multinomial:** $P(z_j = (k \neq K)|x;\theta_{F^k_{z|x,j}}) = \frac{\exp\left(g(x)\theta_{F^k_{z|x,j}}\right)}{1+\sum_{\ell=1}^{K-1}\exp\left(g(x)\theta_{F^\ell_{z|x,j}}\right)}$

Waitlist Decision Graph

A2.1: Waitlist-Dynamic Likelihood

$$\mathcal{L}^U_{N_1}(\theta) = \prod_{n=1}^{N_3} f_{z|x}(z_n|x_n;\theta_{F_{z|x}}) f_{\ddot{m}_2|x,z}(\ddot{m_2}_{,n}|x_n, z_n; \theta_{F_{\ddot{m}_2|x,z}}) f_{\overline{m_{2A}}|\ddot{m}_2}(\overline{m_{2A,n}}|\ddot{m_2}_{,n}; \theta_{F_{\overline{m_{2A}}|\ddot{m}_2}})$$

$$P_{d_{1,n}}(\theta_T)(1 - P_{d_{2,n}}(\theta_{A_2}))P_{d_{3,n}}(\theta_{A_3})^{\mathbb{1}(d_{3,n}=A)}(1 - P_{d_{3,n}}(\theta_{A_3}))^{\mathbb{1}(d_{3,n}=R)} P_{y_n}(\theta_S)^{\mathbb{1}(y_n=S)}(1 - P_{y_n}(\theta_S))^{\mathbb{1}(y_n=F)}$$

$$\prod_{n=N_3+1}^{N_2} f_{z|x}(z_n|x_n;\theta_{F_{z|x}}) f_{\ddot{m}_2|x,z}(\ddot{m_2}_{,n}|x_n, z_n; \theta_{F_{\ddot{m}_2|x,z}}) f_{\overline{m_{2A}}|\ddot{m}_2}(\overline{m_{2A,n}}|\ddot{m_2}_{,n}; \theta_{F_{\overline{m_{2A}}|\ddot{m}_2}})$$

$$P_{d_{1,n}}(\theta_T)P_{d_{2,n}}(\theta_{A_2})P_{y_n}(\theta_S)^{\mathbb{1}(y_n=S)}(1 - P_{y_n}(\theta_S))^{\mathbb{1}(y_n=F)}$$

$$\prod_{n=N_2+1}^{N_1} f_{z|x}(z_n|x_n;\theta_{F_{z|x}}) f_{\ddot{m}_2|x,z}(\ddot{m_2}_{,n}|x_n, z_n; \theta_{F_{\ddot{m}_2|x,z}})(1 - P_{d_{1,n}}(\theta_T))$$

- For $\mathcal{L}_R$, use (θ^U_F,θ^U_S) as initial guess of (θ^R_F,θ^R_S)
- Heckman corrections may be necessary, such as for $f_{z|x}$ and $f_{\ddot{m}_2|x,z}$

Maximum Likelihood Estimation

A2.1: Full Waitlist Model 1

Round 3:

$$v_3(x,z,\overline{m_{2A}},n_3,\overline{q_3},\overline{m_3},\epsilon_3) = \max_{d_3\in\{A,R\}} u_3(x,z,\overline{m_{2A}},n_3,\overline{q_3},\overline{m_3},d_3) + \epsilon_3(d_3), \text{ such that:}$$

$$u_3(x,z,\overline{m_{2A}},n_3,\overline{q_3},\overline{m_3},d_3) = P(y=S|x,z)\mathbb{1}(d_3=A) + P(y_3^*=S|\overline{m_{2A}},n_3,\overline{q_3},\overline{m_3})\mathbb{1}(d_3=R)$$

Round 2:

$$v_2(x,z,\ddot{m}_2,n_2,\overline{q_2},\overline{m_2},\epsilon_2) = \max_{d_2\in\{A,W\}} u_2(x,z,\ddot{m}_2,n_2,\overline{q_2},\overline{m_2},d_2) + \epsilon_2(d_2), \text{ such that:}$$

$$u_2(x,z,\ddot{m}_2,n_2,\overline{q_2},\overline{m_2},d_2) = P(y=S|x,z)\mathbb{1}(d_2=A) + \beta\mathbb{E}[v_3(x,z,\overline{m_{2A}},n_3,\overline{q_3},\overline{m_3},\epsilon_3)|x,z,\ddot{m}_2,n_2,\overline{q_2},\overline{m_2}]\mathbb{1}(d_2=W), \text{such that:}$$

$$\mathbb{E}[v_3(x,z,\overline{m_{2A}},n_3,\overline{q_3},\overline{m_3},\epsilon_3)|x,z,\ddot{m}_2,n_2,\overline{q_2},\overline{m_2}] =$$

$$\int_{\widetilde{\overline{m_3}}}\int_{\widetilde{\overline{q_3}}}\int_{\widetilde{n_3}}\int_{\widetilde{\overline{m_{2A}}}} \sigma \log\left(\sum_{\widetilde{d_3}\in\{A,R\}} e^{u_3(x,z,\widetilde{\overline{m_{2A}}},\widetilde{n_3},\widetilde{\overline{q_3}},\widetilde{\overline{m_3}},\widetilde{d_3})/\sigma}\right) dF_{\overline{m_{2A}}|\ddot{m}_2}(\widetilde{\overline{m_{2A}}}|\ddot{m}_2)\, dF_{n_3|n_2}(\widetilde{n_3}|n_2)\, dF_{\overline{q_3}|\overline{q_2}}(\widetilde{\overline{q_3}}|\overline{q_2})\, dF_{\overline{m_3}|\overline{m_2}}(\widetilde{\overline{m_3}}|\overline{m_2})$$

▸▸ Waitlist Decision Graph

A2.1: Full Waitlist Model 2

Round 1:

$$v_1(x, t, n_1, \overline{q_1}, \overline{m_1}, \epsilon_1) = \max_{d_1 \in \{T,R\}} u_1(x, t, n_1, \overline{q_1}, \overline{m_1}, d_1) + \epsilon_1(d_1), \text{ such that:}$$

- **Hybrid:** $u_1(x, t, d_1) = P(y = S|x)\mathbb{1}(d_1 = T) + P(y_1^* = S|t)\mathbb{1}(d_1 = R)$
- **Dynamic:** $u_1(x, t, n_1, \overline{q_1}, \overline{m_1}, d_1) = \mathbb{E}[v_2(x, z, \ddot{m}_2, n_2, \overline{q_2}, \overline{m_2}, \epsilon_2)|x, n_1, \overline{q_1}, \overline{m_1}]\mathbb{1}(d_1 = T) + L(y_1^* = S|t)\mathbb{1}(d_1 = R)$, such that:

$$\mathbb{E}[v_2(x, z, \ddot{m}_2, n_2, \overline{q_2}, \overline{m_2}, \epsilon_2)|x, n_1, \overline{q_1}, \overline{m_1}] =$$

$$\int_{\widetilde{\overline{m_2}}}\int_{\widetilde{\overline{q_2}}}\int_{\widetilde{n_2}}\int_{\widetilde{z}}\int_{\widetilde{\ddot{m}_2}} \sigma \log\left(\sum_{\widetilde{d_2} \in \{A,R\}} e^{u_2(x, \widetilde{z}, \widetilde{\ddot{m}_2}, \widetilde{n_2}, \widetilde{\overline{q_2}}, \widetilde{\overline{m_2}}, \widetilde{d_2})/\sigma}\right) dF_{\ddot{m}_2|x,z}(\widetilde{\ddot{m}_2}|x, \widetilde{z}) dF_{z|x}(\widetilde{z}|x) dF_{n_2|n_1}(\widetilde{n_2}|n_1) dF_{\overline{q_2}|\overline{q_1}}(\widetilde{\overline{q_2}}|\overline{q_1}) dF_{\overline{m_2}|\overline{m_1}}(\widetilde{\overline{m_2}}|\overline{m_1})$$

Conditional Choice Probabilities:

$$P(d_r|\text{states}) = \frac{\exp(u_r(\text{states}, d_r)/\sigma)}{\sum_{\widetilde{d_r} \in D_r} \exp(u_r(\text{states}, \widetilde{d_r})/\sigma)}$$

Waitlist Decision Graph

A2.1: Full Waitlist-Dynamic Parameterization 1

Unrestricted CCPs:

$$P_{d_1} = P\left(d_1 = T \middle| x, t, n_1, \overline{q_1}, \overline{m_1}; \theta_T\right) = \frac{\exp(f_T(x, t, n_1, \overline{q_1}, \overline{m_1})\theta_T)}{1 + \exp(f_T(x, t, n_1, \overline{q_1}, \overline{m_1})\theta_T)}$$

$$P_{d_2} = P\left(d_2 = A \middle| x, z, \ddot{m}_2, n_2, \overline{q_2}, \overline{m_2}; \theta_{A_2}\right) = \frac{\exp(f_{A_2}(x, z, \ddot{m}_2, n_2, \overline{q_2}, \overline{m_2})\theta_{A_2})}{1 + \exp(f_{A_2}(x, z, \ddot{m}_2, n_2, \overline{q_2}, \overline{m_2})\theta_{A_2})}$$

$$P_{d_3} = P\left(d_3 = A \middle| x, z, \overline{m_{2A}}, n_3, \overline{q_3}, \overline{m_3}; \theta_{A_3}\right) = \frac{\exp(f_{A_3}(x, z, \overline{m_{2A}}, n_3, \overline{q_3}, \overline{m_3})\theta_{A_3})}{1 + \exp(f_{A_3}(x, z, \overline{m_{2A}}, n_3, \overline{q_3}, \overline{m_3})\theta_{A_3})}$$

Success Probability:

$$P_y = P\left(y = S \middle| x, z; \theta_S\right) = \frac{\exp(f_S(x, z)\theta_S)}{1 + \exp(f_S(x, z)\theta_S)}$$

Cutoff Levels/Probabilities:

$$L_{y_1^*} = L\left(y_1^* = S \middle| t; \theta_{S_1^*}\right) = \exp(f_{S_1^*}(t)\theta_{S_1^*})$$

$$P_{y_3^*} = P\left(y_3^* = S \middle| \overline{m_{2A}}, n_3, \overline{q_3}, \overline{m_3}; \theta_{S_3^*}\right) = \frac{\exp(f_{S_3^*}(\overline{m_{2A}}, n_3, \overline{q_3}, \overline{m_3})\theta_{S_3^*})}{1 + \exp(f_{S_3^*}(\overline{m_{2A}}, n_3, \overline{q_3}, \overline{m_3})\theta_{S_3^*})}$$

Waitlist Decision Graph

A2.1: Full Waitlist-Dynamic Parameterization 2

★ Assume $(z, \ddot{m}_2, n_2, \overline{q_2}, \overline{m_2})$ and $(\overline{m_{2A}}, n_3, \overline{q_3}, \overline{m_3})$ are mutually conditionally independent:

$$\mathbb{E}[v_2(x, z, \ddot{m}_2, n_2, \overline{q_2}, \overline{m_2}, \epsilon_2)|x, n_1, \overline{q_1}, \overline{m_1}] = \int_{\widetilde{\overline{m_2}}} \int_{\widetilde{\overline{q_2}}} \int_{\widetilde{n_2}} \int_{\widetilde{z}} \int_{\widetilde{\ddot{m}_2}} \sigma \log \left(\sum_{\widetilde{d_2} \in \{A,R\}} e^{u_2(x, \widetilde{z}, \widetilde{\ddot{m}_2}, \widetilde{n_2}, \widetilde{\overline{q_2}}, \widetilde{\overline{m_2}}, \widetilde{d_2})/\sigma} \right)$$

$$dF_{\ddot{m}_2|x,z}(\widetilde{\ddot{m}_2}|x, \widetilde{z}) dF_{z|x}(\widetilde{z}|x) dF_{n_2|n_1}(\widetilde{n_2}|n_1) dF_{\overline{q_2}|\overline{q_1}}(\widetilde{\overline{q_2}}|\overline{q_1}) dF_{\overline{m_2}|\overline{m_1}}(\widetilde{\overline{m_2}}|\overline{m_1}) = \int_{\widetilde{\overline{m_2}}} \int_{\widetilde{\overline{q_2}}} \int_{\widetilde{n_2}} \int_{\widetilde{z_1}} \cdots \int_{\widetilde{z_{J_z}}} \int_{\widetilde{\ddot{m}_2}} \left[\cdot \right]$$

$$dF_{\ddot{m}_2|x,z}(\widetilde{\ddot{m}_2}|x, \widetilde{z}) dF_{z|x,1}(\widetilde{z_1}|\widetilde{z_2}, \ldots, \widetilde{z_{J_z}}, x) \cdots dF_{z|x,J_z}(\widetilde{z_{J_z}}|x) dF_{n_2|n_1}(\widetilde{n_2}|n_1) dF_{\overline{q_2}|\overline{q_1}}(\widetilde{\overline{q_2}}|\overline{q_1}) dF_{\overline{m_2}|\overline{m_1}}(\widetilde{\overline{m_2}}|\overline{m_1})$$

$$\mathbb{E}[v_3(x, z, \overline{m_{2A}}, n_3, \overline{q_3}, \overline{m_3}, \epsilon_3)|x, z, \ddot{m}_2, n_2, \overline{q_2}, \overline{m_2}] =$$

$$\int_{\widetilde{\overline{m_3}}} \int_{\widetilde{\overline{q_3}}} \int_{\widetilde{n_3}} \int_{\widetilde{\overline{m_{2A}}}} \sigma \log \left(\sum_{\widetilde{d_3} \in \{A,R\}} e^{u_3(x, z, \widetilde{\overline{m_{2A}}}, \widetilde{n_3}, \widetilde{\overline{q_3}}, \widetilde{\overline{m_3}}, \widetilde{d_3})/\sigma} \right) dF_{\overline{m_{2A}}|\ddot{m}_2}(\widetilde{\overline{m_{2A}}}|\ddot{m}_2) dF_{n_3|n_2}(\widetilde{n_3}|n_2) dF_{\overline{q_3}|\overline{q_2}}(\widetilde{\overline{q_3}}|\overline{q_2}) dF_{\overline{m_3}|\overline{m_2}}(\widetilde{\overline{m_3}}|\overline{m_2})$$

- **Continuous:** $f_{z|x}(z_j|x; \beta_{F_{z|x,j}}, \sigma^2_{F_{z|x,j}}) = \frac{1}{\sqrt{2\pi\sigma^2_{F_{z|x,j}}}} \exp\left[\frac{-1}{2\sigma^2_{F_{z|x,j}}} (z_j - g(x)\beta_{F_{z|x,j}})^2 \right]$
- **Binary:** $P(z_j = 1|x; \theta_{F_{z|x,j}}) = \frac{\exp\left(g(x)\theta_{F_{z|x,j}}\right)}{1 + \exp\left(g(x)\theta_{F_{z|x,j}}\right)}$
- **Multinomial:** $P(z_j = (k \neq K)|x; \theta_{F^k_{z|x,j}}) = \frac{\exp\left(g(x)\theta_{F^k_{z|x,j}}\right)}{1 + \sum_{\ell=1}^{K-1} \exp\left(g(x)\theta_{F^\ell_{z|x,j}}\right)}$

▸▸ Waitlist Decision Graph

A2.1: Full Waitlist-Dynamic Likelihood

$$
\begin{aligned}
\mathcal{L}^U_{N_1}(\theta) = \prod_{n=1}^{N_3} & f_{z|x}(z_n|x_n;\theta_{F_{z|x}}) f_{\ddot{m}_2|x,z}(\ddot{m}_{2,n}|x_n,z_n;\theta_{F_{\ddot{m}_2|x,z}}) f_{n_2|n_1}(n_{2,n}|n_{1,n};\theta_{F_{n_2|n_1}}) f_{\overline{q_2}|\overline{q_1}}(\overline{q_{2,n}}|\overline{q_{1,n}};\theta_{F_{\overline{q_2}|\overline{q_1}}}) f_{\overline{m_2}|\overline{m_1}}(\overline{m_{2,n}}|\overline{m_{1,n}};\theta_{F_{\overline{m_2}|\overline{m_1}}}) \\
& f_{\overline{m_{2A}}|\ddot{m}_2}(\overline{m_{2A,n}}|\ddot{m}_{2,n};\theta_{F_{\overline{m_{2A}}|\ddot{m}_2}}) f_{n_3|n_2}(n_{3,n}|n_{2,n};\theta_{F_{n_3|n_2}}) f_{\overline{q_3}|\overline{q_2}}(\overline{q_{3,n}}|\overline{q_{2,n}};\theta_{F_{\overline{q_3}|\overline{q_2}}}) f_{\overline{m_3}|\overline{m_2}}(\overline{m_{3,n}}|\overline{m_{2,n}};\theta_{F_{\overline{m_3}|\overline{m_2}}}) \\
& P_{d_{1,n}}(\theta_T)(1-P_{d_{2,n}}(\theta_{A_2}))P_{d_{3,n}}(\theta_{A_3})^{\mathbb{1}(d_{3,n}=A)}(1-P_{d_{3,n}}(\theta_{A_3}))^{\mathbb{1}(d_{3,n}=R)} P_{y_n}(\theta_S)^{\mathbb{1}(y_n=S)}(1-P_{y_n}(\theta_S))^{\mathbb{1}(y_n=F)} \\
\prod_{n=N_3+1}^{N_2} & f_{z|x}(z_n|x_n;\theta_{F_{z|x}}) f_{\ddot{m}_2|x,z}(\ddot{m}_{2,n}|x_n,z_n;\theta_{F_{\ddot{m}_2|x,z}}) f_{n_2|n_1}(n_{2,n}|n_{1,n};\theta_{F_{n_2|n_1}}) f_{\overline{q_2}|\overline{q_1}}(\overline{q_{2,n}}|\overline{q_{1,n}};\theta_{F_{\overline{q_2}|\overline{q_1}}}) f_{\overline{m_2}|\overline{m_1}}(\overline{m_{2,n}}|\overline{m_{1,n}};\theta_{F_{\overline{m_2}|\overline{m_1}}}) \\
& f_{\overline{m_{2A}}|\ddot{m}_2}(\overline{m_{2A,n}}|\ddot{m}_{2,n};\theta_{F_{\overline{m_{2A}}|\ddot{m}_2}}) f_{n_3|n_2}(n_{3,n}|n_{2,n};\theta_{F_{n_3|n_2}}) f_{\overline{q_3}|\overline{q_2}}(\overline{q_{3,n}}|\overline{q_{2,n}};\theta_{F_{\overline{q_3}|\overline{q_2}}}) f_{\overline{m_3}|\overline{m_2}}(\overline{m_{3,n}}|\overline{m_{2,n}};\theta_{F_{\overline{m_3}|\overline{m_2}}}) \\
& P_{d_{1,n}}(\theta_T)P_{d_{2,n}}(\theta_{A_2})P_{y_n}(\theta_S)^{\mathbb{1}(y_n=S)}(1-P_{y_n}(\theta_S))^{\mathbb{1}(y_n=F)} \prod_{n=N_2+1}^{N_1} f_{z|x}(z_n|x_n;\theta_{F_{z|x}}) f_{\ddot{m}_2|x,z}(\ddot{m}_{2,n}|x_n,z_n;\theta_{F_{\ddot{m}_2|x,z}}) \\
& f_{n_2|n_1}(n_{2,n}|n_{1,n};\theta_{F_{n_2|n_1}}) f_{\overline{q_2}|\overline{q_1}}(\overline{q_{2,n}}|\overline{q_{1,n}};\theta_{F_{\overline{q_2}|\overline{q_1}}}) f_{\overline{m_2}|\overline{m_1}}(\overline{m_{2,n}}|\overline{m_{1,n}};\theta_{F_{\overline{m_2}|\overline{m_1}}})(1-P_{d_{1,n}}(\theta_T))
\end{aligned}
$$

- For $\mathcal{L}^R$ and $\mathcal{L}^U$, estimate θ^U_S with 1st-stage likelihood to get $\overline{q}$ = current year's $\overline{P_{y_n}}$: $\mathcal{L}^P_{N_2}(\theta_S) = \prod_{n=1}^{N_2} P_{y_n}(\theta_S)^{\mathbb{1}(y_n=S)}(1-P_{y_n}(\theta_S))^{\mathbb{1}(y_n=F)}$

Maximum Likelihood Estimation

A2.1: Waitlist Notes: Memory and Dynamics

- **Memory:** Need at least 5 years of data to identify all parameters
  - For simplicity with simulated data, suppose committee provides m_2. But to estimate m_2 with actual data, estimate matriculation parameters in first-stage likelihood
- **Dynamics:** What if committee doesn't think dynamically?
  - If $\ddot{m}_2$ increasing increases $\overline{F}_{\overline{m_{2A}}|\ddot{m}_2}$, which increases $\mathbb{E}[P(\text{Cutoff})_3]$, then it should
  - Don't need success data for all years to identify these two effects
- **Over/Undershooting:** Committee may wish to avoid both
  - To Round 3's $P(\text{Cutoff})$, add target cohort size minus number of early matriculants
  - Penalty parameter may be unidentifiable, so may have to calibrate it

Waitlist Memory and Dynamics

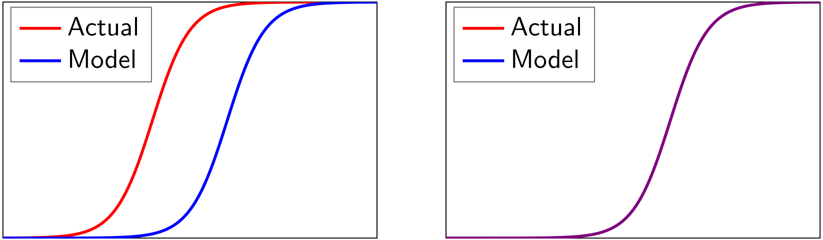
A2.1: Optimality Tests Notes

1. **Likelihood-Ratio:** Restricted model not nested in unrestricted model (Vuong 1989)
   - **Program Fit:** Does model fit program's behavior?
     - $d_1 = \mathbb{1}(\text{Transition})$, $d_2 = \mathbb{1}(\text{Accept})$
     - If not, could program be behaving suboptimally (Simon 1956)?
   - **Profession Fit:** Does model fit profession's behavior?
     - $d_2 = \mathbb{1}(\text{AttendProgram})$ but d_1 unobservable, so must estimate one-stage model
2. **Deviation Gains:** Adjust θ_{S^*} so transition and acceptance rates are unchanged
   - **Year-Static:** Rank all applicants by $P(y = S|x)$, set $\theta_{S_1^*}$ to match transition rate, rank survivors by $P(S|x, z)$, and set $\theta_{S_2^*}$ to match acceptance rate
   - **Year-Dynamic:** Use MSM to estimate new $(\theta_{S_1^*}, \theta_{S_2^*})$; moments are each year's transition and acceptance rates. But counterfactual does not require $(\hat{\theta}_{S_1^*}, \hat{\theta}_{S_2^*})$

Optimality Tests

A2.1: How Deviation Gains Test Works

1. Write Bellman equations for committee's optimization problem
2. Estimate parameters. Rationality assumption distorts estimates
3. Re-estimate parameters without rationality, and use to solve model
4. Compare selections from model's decision rule to actual decision rule
5. To prevent overfitting, use perturbations of estimates for comparison



Non-Optimizing Committee

Optimizing Committee

Deviation Gains Interpretation

A2.1: Deviation Gains Algorithm 1

Year-Static/Dynamic/Myopic:

1. Rank applicants in each year by $P(y = S|x)$ for static, or $\mathbb{E}[v_2(x, z, \epsilon_2)|x]$ for dynamic and myopic. Transition top N_T applicants, and reject the rest
2. Rank surviving applicants by $P(y = S|x, z)$, and accept top N_A survivors. Compute $\overline{P(y = S|x, z)}$ of acceptance set, and compare to committee's set

Deviation Gains Interpretation

A2.1: Deviation Gains Algorithm 2

Waitlist-Hybrid/Dynamic:

1. Rank applicants in each year by $P(y = S|x)$ for hybrid, or $\mathbb{E}[v_2(x, z, \ddot{m}_2, \epsilon_2)|x]$ for dynamic. Transition top N_T applicants, and reject the rest
2. Rank surviving applicants by $P(y = S|x, z) - \beta\mathbb{E}[v_3(x, z, \overline{m_{2A}}, \epsilon_3)|x, z, \ddot{m}_2]$. Accept top N_{2A} survivors, and waitlist the rest
3. Rank early acceptances by matriculation score m. All early acceptances with m at least as high as committee's marginal early matriculant matriculate
4. Rank waitlisted applicants by $P(y = S|x, z)$. Increase/decrease N_{3A} to N'_{3A} depending on how many spots remain relative to committee
5. Rank late acceptances by m. Top ones matriculate until cohort is filled. Compute $\overline{P(y = S|x, z)}$ of matriculation set, and compare to committee's set

Deviation Gains Interpretation

A2.1: Randomization Tests 1

Theorem 4 (Proof)

Let d^R be the model's decision rule, and d^U the actual decision rule. By optimality:

$$\frac{1}{N_A}\sum_{n=1}^{N} P\left(y_n = S \middle| x_n, z_n; \hat{\theta}_S^U\right) \mathbb{1}\left\{d_{1,n}\left[P_{y_n}\left(\hat{\theta}^U\right)\right] = T, d_{2,n}^R\left[P_{y_n}\left(\hat{\theta}_S^U\right)\right] = A\right\}$$

$$\geq \frac{1}{N_A}\sum_{n=1}^{N} P\left(y_n = S \middle| x_n, z_n; \hat{\theta}_S^U\right) \mathbb{1}\left\{d_{1,n}\left[P_{y_n}\left(\hat{\theta}^U\right)\right] = T, d_{2,n}^U\left[P_{y_n}\left(\hat{\theta}_A^U\right)\right] = A\right\}$$

- But for perturbation $\widetilde{\theta_{S,t}^U}$ of $\hat{\theta}_S^U$'s asymptotic distribution, can have:

$$\frac{1}{N_A}\sum_{n=1}^{N} P\left(y_n = S \middle| x_n, z_n; \widetilde{\theta_{S,t}^U}\right) \mathbb{1}\left\{d_{1,n}\left[P_{y_n}\left(\hat{\theta}_U\right)\right] = T, d_{2,n}^R\left[P_{y_n}\left(\hat{\theta}_S^U\right)\right] = A\right\}$$

$$< \frac{1}{N_A}\sum_{n=1}^{N} P\left(y_n = S \middle| x_n, z_n; \widetilde{\theta_{S,t}^U}\right) \mathbb{1}\left\{d_{1,n}\left[P_{y_n}\left(\hat{\theta}_U\right)\right] = T, d_{2,n}^U\left[P_{y_n}\left(\hat{\theta}_A^U\right)\right] = A\right\}$$

- For waitlist models, compare matriculants, not acceptances

Deviation Gains Interpretation

A2.1: Randomization Tests 2

- **Question:** Are deviation gains robust to estimation error?
- **Test 1:** Across T perturbations, plot CDFs of $\overline{P(\text{Success})}$ of both acceptance sets. Does the model's CDF stochastically dominate the actual decision rule's CDF?
- **Test 2:** Two-sample Kolmogorov-Smirnov test of equality of CDFs:
  - Let $X = \overline{P_y\left[d\left(\hat{\theta}^U\right), \widetilde{\theta_S^U}\right]}$, and $F_T(x)$ be X's CDF over T perturbations
  - Then $D_T = \sup_x \left|F_T^R(x) - F_T^U(x)\right|$. Reject equality if $D_T > \sqrt{\frac{-\log(\alpha/2)}{T}}$
- **Open Question:** Would deviation gains be borne out in practice?

▸▸ Deviation Gains Interpretation

A2.1: Summary of Results

- **Results:** Estimation results are well behaved
  - **Year-Static:** Likelihood-ratio test rejects and deviation gains statistically significant only for simulated dataset where committee misvalues applicant characteristics
  - **Year-Dynamic:** Likelihood-ratio test always rejects, but gains exist only for non-optimizing dataset. Gains are slightly larger than in year-myopic model
  - **Waitlist-Hybrid/Dynamic:** Matriculation estimates are as expected
- Example of cutoff probability reversal if committee transitions few files in Round 1:
  - Three applicants: A, B, and C. Committee transitions two, accepts one
  - A is best and C is worst overall, but A is worst in objective variables
  - Committee rejects A in Round 1 and accepts B, who is worse than A
  - By assuming h hours to read application file and w hourly wage, and calculating model's $\overline{P(\text{Success})}$ induced by all possible N_T, can put dollar value on success

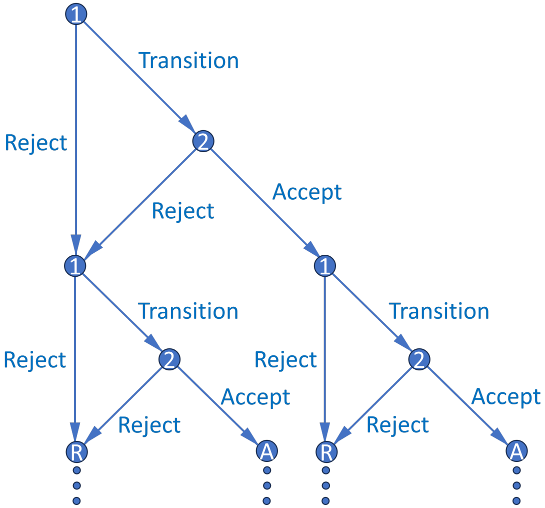
Conclusion

A2.1: Extensions

- **Extension 1:** Create matriculation score uncorrelated with P(Success)
  - For accepted applicants, use matriculation predictors in essays/rec letters
  - Can help committee find "people that we can afford" (*Moneyball*)
- **Extension 2:** Relax assumption that committee maximizes P(Success)
  - Instead maximize convex combination of P(Success) and other objectives
  - **Example:** Committee may want diverse cohort (e.g. across fields): $\alpha P(\text{Success}) + (1-\alpha)\text{Diversity}$, where $\alpha \in [0,1]$ can be estimated
- **Extension 3:** Multiyear models (see Appendix 2.2)
  - Two-round models repeat over infinite horizon with discounting
  - States contain info about past years/rounds, and committee values future years/rounds (memory includes matriculation score and diversity)

Conclusion

A2.2: Multiyear Decision Graph



⏩ Conclusion

A2.2: Multiyear Memory (Matriculation)

- Suppose committee maximizes discounted "lifetime" cohort success
- Respecify $P(y_2^* = S|t)$, where $t =$ year, as $L(y_2^* = S|\overline{q}, M, c_{-1})$
  - $\overline{q} =$ current year's average surviving applicant quality (i.e. average $P(\text{Success})$)
  - $M =$ current year's number of surviving applicants
  - $c_{-1} =$ previous year's cohort size
  - $L(\text{Cutoff}_2)$ increases in all three. In particular, in increases in c_{-1} because committee must keep number of total students in program relatively constant
- What information available at start of Round 2 determines c?
  - **Always:** $\overline{m} =$ average surviving applicant matriculation score
  - **If and only if $d_2 = A$:** $m =$ applicant's matriculation score

Conclusion

A2.2: Multiyear Dynamics (Matriculation)

Theorem 5 (Proof)

Success probability equal, an applicant's Round 2 acceptance probability is strictly increasing in their matriculation score.

- With memory, optimal dynamic decision may not equal optimal myopic one
  - May accept applicant with high m even if $P(\text{Success}) < L(\text{Cutoff}_2)$
  - High m means high $\overline{F}_{c|m}$, which means high $\mathbb{E}[L(\text{Cutoff}_2)']$ and future EV
  - Accepting applicants who will matriculate helps avoid future TA shortages, and accepting more applicants next year is undesirable if there's any risk aversion
- Harder to estimate since multiyear problem has no closed-form solution
  - Reduced-form results and factor analysis can help reduce dimensionality

Conclusion

A2.2: Multiyear Model (Matriculation), Round 2

$$v_2(x, z, m, \overline{m}, \overline{q}, M, c_{-1}, \epsilon_2) = \max_{d_2 \in \{A,R\}} u_2(x, z, m, \overline{m}, \overline{q}, M, c_{-1}, d_2) + \epsilon_2(d_2), \text{ such that:}$$

$$\begin{aligned} u_2(x, z, m, \overline{m}, \overline{q}, M, c_{-1}, d_2) = &\{P(y = S|x, z) + \beta\mathbb{E}[v_1(x', t', c, {\epsilon_1}')|m, \overline{m}]\}\mathbb{1}(d_2 = A) \\ &+ \{L(y_2^* = S|\overline{q}, M, c_{-1}) + \beta\mathbb{E}[v_1(x', t', c, {\epsilon_1}')|\overline{m}]\}\mathbb{1}(d_2 = R), \text{ such that:} \end{aligned}$$

$$\mathbb{E}[v_1(x', t', c, {\epsilon_1}')|(m), \overline{m}] = \int_c \int_{t'} \int_{x'} \sigma \log \left(\sum_{{d_1}' \in \{T,R\}} e^{u_1(x', t', c, {d_1}')/\sigma} \right) dF_x(x') dF_t(t') dF_{c|(m),\overline{m}}(c|(m), \overline{m})$$

Conditional Choice Probabilities:

$$P(d_2|x, z, m, \overline{m}, \overline{q}, M, c_{-1}) = \frac{\exp(u_2(x, z, m, \overline{m}, \overline{q}, M, c_{-1}, d_2)/\sigma)}{\sum_{\widetilde{d}_2 \in \{A,R\}} \exp(u_2(x, z, m, \overline{m}, \overline{q}, M, c_{-1}, \widetilde{d}_2)/\sigma)}$$

Conclusion

A2.2: Multiyear Model (Matriculation), Round 1

$$v_1(x, t, c_{-1}, \epsilon_1) = \max_{d_1 \in \{T,R\}} u_1(x, t, c_{-1}, d_1) + \epsilon_1(d_1), \text{ such that:}$$

$$u_1(x, t, c_{-1}, d_1) = \mathbb{E}[v_2(x, z, m, \overline{m}, \overline{q}, M, c_{-1}, \epsilon_2)|x, c_{-1}]\mathbb{1}(d_1 = T) + \{L(y_1^* = S|t) + \beta\mathbb{E}[v_1(x', t', c, \epsilon_1{}')|\overline{m}]\}\mathbb{1}(d_1 = R), \text{ such that:}$$

$$\mathbb{E}[v_2(x, z, m, \overline{m}, \overline{q}, M, c_{-1}, \epsilon_2)|x, c_{-1}] = \int_{\widetilde{M}}\int_{\widetilde{\overline{q}}}\int_{\widetilde{\overline{m}}}\int_{\widetilde{m}}\int_{\widetilde{z}} \sigma \log\left(\sum_{\widetilde{d}_2 \in \{A,R\}} e^{u_2(x,\widetilde{z},\widetilde{m},\widetilde{\overline{m}},\widetilde{\overline{q}},\widetilde{M},c_{-1},\widetilde{d}_2)/\sigma}\right) dF_{z|x}(\widetilde{z}|x) dF_{m|x}(\widetilde{m}|x) dF_{\overline{m}}(\widetilde{\overline{m}}) dF_{\overline{q}}(\widetilde{\overline{q}}) dF_M(\widetilde{M})$$

Conditional Choice Probabilities:

$$P(d_1|x, t, c_{-1}) = \frac{\exp(u_1(x, t, c_{-1}, d_1)/\sigma)}{\sum_{\widetilde{d}_1 \in \{T,R\}} \exp(u_1(x, t, c_{-1}, \widetilde{d}_1)/\sigma)}$$

Conclusion

A2.2: Multiyear (Matriculation) Parameterization 1

Unrestricted CCPs:

$$P_{d_1} = P\left(d_1 = T \middle| x, t, c_{-1}; \theta_T\right) = \frac{\exp(f_T(x, t, c_{-1})\theta_T)}{1 + \exp(f_T(x, t, c_{-1})\theta_T)}$$

$$P_{d_2} = P\left(d_2 = A \middle| x, z, m, \overline{m}, \overline{q}, M, c_{-1}; \theta_A\right) = \frac{\exp(f_A(x, z, m, \overline{m}, \overline{q}, M, c_{-1})\theta_A)}{1 + \exp(f_A(x, z, m, \overline{m}, \overline{q}, M, c_{-1})\theta_A)}$$

Success Probability:

$$P_y = P\left(y = S \middle| x, z; \theta_S\right) = \frac{\exp(f_S(x, z)\theta_S)}{1 + \exp(f_S(x, z)\theta_S)}$$

Cutoff Levels:

$$L_{y_1^*} = L\left(y_1^* = S \middle| t; \theta_{S_1^*}\right) = f_{S_1^*}(t)\theta_{S_1^*}$$

$$L_{y_2^*} = L\left(y_2^* = S \middle| \overline{q}, M, c_{-1}; \theta_{S_2^*}\right) = f_{S_2^*}(\overline{q}, M, c_{-1})\theta_{S_2^*}$$

Conclusion

A2.2: Multiyear (Matriculation) Parameterization 2.1

★ Assume (x, t) mutually independent, and next year independent of current year:

$$\mathbb{E}[v_1(x', t', c, \epsilon_1')|(m), \overline{m}] = \int_c \int_{t'} \int_{x'} \sigma \log \left(\sum_{d_1' \in \{T,R\}} e^{u_1(x',t',c,d_1')/\sigma} \right) dF_x(x') dF_t(t') dF_{c|(m),\overline{m}}(c|(m), \overline{m})$$

$$= \int_c \int_{t_1'} \cdots \int_{t_{J_t}'} \int_{x_1'} \cdots \int_{x_{J_x}'} \Big[\cdot\Big] dF_{x,1}(x_1'|x_2', \ldots, x_{J_x}') \cdots dF_{x,J_x}(x_{J_x}') dF_{t,1}(t_1'|t_2', \ldots, t_{J_t}') \cdots dF_{t,J_t}(t_{J_t}') dF_{c|(m),\overline{m}}(c|(m), \overline{m})$$

- **Continuous:** $f_x(x_j; \beta_{F_{x,j}}, \sigma^2_{F_{x,j}}) = \frac{1}{\sqrt{2\pi\sigma^2_{F_{x,j}}}} \exp\left[\frac{-1}{2\sigma^2_{F_{x,j}}}(x_j - \beta_{F_{x,j}})^2\right]$
- **Binary:** $P(x_j = 1; \theta_{F_{x,j}}) = \frac{\exp\left(\theta_{F_{x,j}}\right)}{1+\exp\left(\theta_{F_{x,j}}\right)}$
- **Multinomial:** $P(x_j = (k \neq K); \theta_{F^k_{x,j}}) = \frac{\exp\left(\theta_{F^k_{x,j}}\right)}{1+\sum_{\ell=1}^{K-1} \exp\left(\theta_{F^\ell_{x,j}}\right)}$

⏩ Conclusion

A2.2: Multiyear (Matriculation) Parameterization 2.2

★ Assume $(z, m, \overline{m}, \overline{q}, M)$ mutually independent such that $(z, m)|x$:

$$\mathbb{E}[v_2(x, z, m, \overline{m}, \overline{q}, M, c_{-1}, \epsilon_2)|x, c_{-1}] =$$

$$\int_{\widetilde{M}} \int_{\widetilde{\overline{q}}} \int_{\widetilde{\overline{m}}} \int_{\widetilde{m}} \int_{\widetilde{z}} \sigma \log \left(\sum_{\widetilde{d}_2 \in \{A,R\}} e^{u_2(x,\widetilde{z},\widetilde{m},\widetilde{\overline{m}},\widetilde{\overline{q}},\widetilde{M},c_{-1},\widetilde{d}_2)/\sigma} \right) dF_{z|x}(\widetilde{z}|x) dF_{m|x}(\widetilde{m}|x) dF_{\overline{m}}(\widetilde{\overline{m}}) dF_{\overline{q}}(\widetilde{\overline{q}}) dF_M(\widetilde{M})$$

$$= \int_{\widetilde{M}} \int_{\widetilde{\overline{q}}} \int_{\widetilde{\overline{m}}} \int_{\widetilde{m}} \int_{\widetilde{z}_1} \cdots \int_{\widetilde{z_{J_z}}} \left[\cdot \right] dF_{z|x,1}(\widetilde{z}_1|\widetilde{z}_2, \ldots, \widetilde{z_{J_z}}, x) \cdots dF_{z|x,J_z}(\widetilde{z_{J_z}}|x) dF_{m|x}(\widetilde{m}|x) dF_{\overline{m}}(\widetilde{\overline{m}}) dF_{\overline{q}}(\widetilde{\overline{q}}) dF_M(\widetilde{M})$$

- **Continuous:** $f_{z|x}(z_j|x; \beta_{F_{z|x,j}}, \sigma^2_{F_{z|x,j}}) = \frac{1}{\sqrt{2\pi\sigma^2_{F_{z|x,j}}}} \exp\left[\frac{-1}{2\sigma^2_{F_{z|x,j}}}(z_j - g(x)\beta_{F_{z|x,j}})^2\right]$
- **Binary:** $P(z_j = 1|x; \theta_{F_{z|x,j}}) = \frac{\exp\left(g(x)\theta_{F_{z|x,j}}\right)}{1+\exp\left(g(x)\theta_{F_{z|x,j}}\right)}$
- **Multinomial:** $P(z_j = (k \neq K)|x; \theta_{F^k_{z|x,j}}) = \frac{\exp\left(g(x)\theta_{F^k_{z|x,j}}\right)}{1+\sum_{\ell=1}^{K-1} \exp\left(g(x)\theta_{F^\ell_{z|x,j}}\right)}$

⏩ Conclusion

A2.2: Multiyear (Matriculation) Likelihood

$$\mathcal{L}_N^U(\theta) = \prod_{n=1}^{N_T} f_x(x_n;\theta_{F_x}) f_t(t_n;\theta_{F_t}) f_{z|x}(z_n|x_n;\theta_{F_{z|x}}) f_{m|x}(m_n|x_n;\theta_{F_{m|x}}) f_{\overline{m}}(\overline{m}_n;\theta_{F_{\overline{m}}}) f_{\overline{q}}(\overline{q}_n;\theta_{F_{\overline{q}}}) f_M(M_n;\theta_{F_M})$$

$$f_{c|m,\overline{m}}(c_n|m_n,\overline{m}_n;\theta_{F_{c|m,\overline{m}}}) P_{d_{1,n}}(\theta_T) P_{d_{2,n}}(\theta_A)^{\mathbb{1}(d_{2,n}=A)} (1-P_{d_{2,n}}(\theta_A))^{\mathbb{1}(d_{2,n}=R)} P_{y_n}(\theta_S)^{\mathbb{1}(y_n=S)} (1-P_{y_n}(\theta_S))^{\mathbb{1}(y_n=F)}$$

$$\prod_{n=N_T+1}^{N} f_x(x_n;\theta_{F_x}) f_t(t_n;\theta_{F_t}) f_{z|x}(z_n|x_n;\theta_{F_{z|x}}) f_{m|x}(m_n|x_n;\theta_{F_{m|x}})(1-P_{d_{1,n}}(\theta_T))$$

- For $\mathcal{L}^R$ and $\mathcal{L}^U$, estimate θ_S^U with 1st-stage likelihood to get $\overline{q}$ = current year's $\overline{P_{y_n}}$: $\mathcal{L}_{N_T}^P(\theta_S) = \prod_{n=1}^{N_T} P_{y_n}(\theta_S)^{\mathbb{1}(y_n=S)}(1-P_{y_n}(\theta_S))^{\mathbb{1}(y_n=F)}$
- As with year-dynamic model, for $\mathcal{L}_R$, use (θ_F^U, θ_S^U) as initial guess of (θ_F^R, θ_S^R)

Conclusion

A2.2: Multiyear Memory and Dynamics (Diversity)

- Let additional state $a =$ any diversity variable affecting success
  - For example, $a = \mathbb{1}(\text{TheoryField})$; theory is less common than applied
  - Let $\bar{a}_{-1} =$ percentage of last year's acceptance set that's theory
  - If $|a - \bar{a}_{-1}|$ is small, $P(\text{Success})$ may decrease because future advisor may be too busy (effect may be unidentifiable if program never gets too imbalanced)

Theorem 6 (Proof)

Consider any two applicants, one with $a = 1$ and one with $a = 0$, but with equal success probabilities and therefore different values of x or z. Suppose $P(a' = 1) = p > 0$. Then for all sufficiently small p, the $a = 1$ applicant has a strictly greater Round 2 acceptance probability.

- Optimal dynamic decision may not equal optimal myopic one. May accept diverse applicant with $P(\text{Success}) < L(\text{Cutoff})$ to increase $P(\text{Success})$ of next year's pool
  - Relative to $a = 0$, $a = 1 \Rightarrow$ higher $\overline{F}_{\bar{a}|a} \Rightarrow$ higher $\mathbb{E}[P(\text{Success})']$ and future EV

Conclusion

A2.2: Multiyear Model (Diversity), Round 2

$$v_2(x, z, a, \bar{a}_{-1}, t, \epsilon_2) = \max_{d_2 \in \{A,R\}} u_2(x, z, a, \bar{a}_{-1}, t, d_2) + \epsilon_2(d_2), \text{ such that:}$$

$$u_2(x, z, a, \bar{a}_{-1}, t, d_2) = \{P(y = S|x, z, |a - \bar{a}_{-1}|) + \beta\mathbb{E}[v_1(x', \bar{a}, t', \epsilon_1')|a]\}\mathbb{1}(d_2 = A) \\ + \{L(y_2^* = S|t) + \beta\mathbb{E}[v_1(x', \bar{a}, t', \epsilon_1')]\}\mathbb{1}(d_2 = R), \text{ such that:}$$

$$\mathbb{E}[v_1(x', \bar{a}, t', \epsilon_1')|a] = \int_{\widetilde{t'}} \int_{\widetilde{\bar{a}}} \int_{\widetilde{x'}} \sigma \log \left(\sum_{d_1' \in \{T,R\}} e^{u_1(\widetilde{x'}, \widetilde{\bar{a}}, \widetilde{t'}, d_1')/\sigma} \right) dF_{x'}(\widetilde{x'}) dF_{\bar{a}|a}(\widetilde{\bar{a}}|a) dF_{t'}(\widetilde{t'})$$

Conditional Choice Probabilities:

$$P(d_2|x, z, a, \bar{a}_{-1}, t) = \frac{\exp(u_2(x, z, a, \bar{a}_{-1}, t, d_2)/\sigma)}{\sum_{\widetilde{d}_2 \in \{A,R\}} \exp(u_2(x, z, a, \bar{a}_{-1}, t, \widetilde{d}_2)/\sigma)}$$

Conclusion

A2.2: Multiyear Model (Diversity), Round 1

$$v_1(x, \bar{a}_{-1}, t, \epsilon_1) = \max_{d_1 \in \{T,R\}} u_1(x, \bar{a}_{-1}, t, d_1) + \epsilon_1(d_1), \text{ such that:}$$

$$u_1(x, \bar{a}_{-1}, t, d_1) = \mathbb{E}[v_2(x, z, a, \bar{a}_{-1}, t, \epsilon_2)|x, \bar{a}_{-1}, t]\mathbb{1}(d_1 = T)$$
$$+ \{L(y_1^* = S|t) + \beta\mathbb{E}[v_1(x', \bar{a}, t', \epsilon_1')]\}\mathbb{1}(d_1 = R), \text{ such that:}$$

$$\mathbb{E}[v_2(x, z, a, \bar{a}_{-1}, t, \epsilon_2)|x, \bar{a}_{-1}, t] = \int_{\widetilde{a}}\int_{\widetilde{z}} \sigma \log\left(\sum_{\widetilde{d}_2 \in A,R} e^{u_2(x,\widetilde{z},\widetilde{a},\bar{a}_{-1},t,\widetilde{d}_2)/\sigma}\right) dF_{z|x}(\widetilde{z}|x)dF_a(\widetilde{a})$$

$$\mathbb{E}[v_1(x', \bar{a}, t', \epsilon_1')] = \int_{\widetilde{t'}}\int_{\widetilde{\bar{a}}}\int_{\widetilde{x'}} \sigma \log\left(\sum_{d_1' \in \{T,R\}} e^{u_1(\widetilde{x'},\widetilde{\bar{a}},\widetilde{t'},d_1')/\sigma}\right) dF_{x'}(\widetilde{x'})dF_{\bar{a}}(\widetilde{\bar{a}})dF_{t'}(\widetilde{t'})$$

Conditional Choice Probabilities:

$$P(d_1|x, \bar{a}_{-1}, t) = \frac{\exp(u_1(x, \bar{a}_{-1}, t, d_1)/\sigma)}{\sum_{\widetilde{d}_1 \in \{T,R\}} \exp(u_1(x, \bar{a}_{-1}, t, \widetilde{d}_1)/\sigma)}$$

Conclusion

A2.2: Multiyears (Diversity) Parameterization 1

Unrestricted CCPs:

$$P_{d_1} = P\left(d_1 = T \middle| x, \bar{a}_{-1}, t; \theta_T\right) = \frac{\exp(f_T(x, \bar{a}_{-1}, t)\theta_T)}{1 + \exp(f_T(x, \bar{a}_{-1}, t)\theta_T)}$$

$$P_{d_2} = P\left(d_2 = A \middle| x, z, a, \bar{a}_{-1}, t; \theta_A\right) = \frac{\exp(f_A(x, z, a, \bar{a}_{-1}, t)\theta_A)}{1 + \exp(f_A(x, z, a, \bar{a}_{-1}, t)\theta_A)}$$

Success Probability:

$$P_y = P\left(y = S \middle| x, z, |a - \bar{a}_{-1}|; \theta_S\right) = \frac{\exp(f_S(x, z, |a - \bar{a}_{-1}|)\theta_S)}{1 + \exp(f_S(x, z, |a - \bar{a}_{-1}|)\theta_S)}$$

Cutoff Levels:

$$L_{y_1^*} = L\left(y_1^* = S \middle| t; \theta_{S_1^*}\right) = f_{S_1^*}(t)\theta_{S_1^*}$$
$$L_{y_2^*} = L\left(y_2^* = S \middle| t; \theta_{S_2^*}\right) = f_{S_2^*}(t)\theta_{S_2^*}$$

Conclusion

A2.2: Multiyear (Diversity) Parameterization 2.1

★ Assume $(x, \bar{a}, t)$ mutually independent such that $\bar{a}|a$, and t' independent of t:

$$\mathbb{E}[v_1(x', \bar{a}, t', \epsilon_1')|a] = \int_{\widetilde{t'}} \int_{\widetilde{\bar{a}}} \int_{\widetilde{x'}} \sigma \log \left(\sum_{d_1' \in \{T,R\}} e^{u_1(\widetilde{x'}, \widetilde{\bar{a}}, \widetilde{t'}, d_1')/\sigma} \right) dF_{x'}(\widetilde{x'}) dF_{\bar{a}|a}(\widetilde{\bar{a}}|a) dF_{t'}(\widetilde{t'}) =$$

$$\int_{\widetilde{t_1'}} \cdots \int_{\widetilde{t_{J_t}'}} \int_{\widetilde{\bar{a}}} \int_{\widetilde{x_1'}} \cdots \int_{\widetilde{x_{J_x}'}} \left[\cdot \right] F_{x,1}({x_1}'|{x_2}', \ldots, {x_{J_x}}') \cdots dF_{x,J_x}({x_{J_x}}') dF_{\bar{a}|a}(\widetilde{\bar{a}}|a) dF_{t,1}({t_1}'|{t_2}', \ldots, {t_{J_t}}') \cdots dF_{t,J_t}({t_{J_t}}')$$

- **Continuous:** $f_x(x_j; \beta_{F_{x,j}}, \sigma^2_{F_{x,j}}) = \frac{1}{\sqrt{2\pi\sigma^2_{F_{x,j}}}} \exp\left[\frac{-1}{2\sigma^2_{F_{x,j}}}(x_j - \beta_{F_{x,j}})^2\right]$
- **Binary:** $P(x_j = 1; \theta_{F_{x,j}}) = \frac{\exp\left(\theta_{F_{x,j}}\right)}{1+\exp\left(\theta_{F_{x,j}}\right)}$
- **Multinomial:** $P(x_j = (k \neq K); \theta_{F^k_{x,j}}) = \frac{\exp\left(\theta_{F^k_{x,j}}\right)}{1+\sum_{\ell=1}^{K-1} \exp\left(\theta_{F^\ell_{x,j}}\right)}$

Conclusion

A2.2: Multiyear (Diversity) Parameterization 2.2

★ Assume (z, a) independent, such that $z|x$:

$$\mathbb{E}[v_2(x, z, a, \bar{a}_{-1}, t, \epsilon_2)|x, \bar{a}_{-1}, t] = \int_{\tilde{a}} \int_{\tilde{z}} \sigma \log \left(\sum_{\tilde{d}_2 \in A,R} e^{u_2(x,\tilde{z},\tilde{a},\bar{a}_{-1},t,\tilde{d}_2)/\sigma} \right) dF_{z|x}(\tilde{z}|x) dF_a(\tilde{a})$$

$$= \int_{\tilde{a}} \int_{\tilde{z}_1} \cdots \int_{\tilde{z}_J} \Big[\cdot \Big] dF_1(\tilde{z}_1|\tilde{z}_2, \ldots \tilde{z}_J, x) \cdots dF_J(\tilde{z}_J|x) dF_a(\tilde{a})$$

- **Continuous:** $f_{z|x}(z_j|x; \beta_{F_{z|x,j}}, \sigma^2_{F_{z|x,j}}) = \frac{1}{\sqrt{2\pi\sigma^2_{F_{z|x,j}}}} \exp\left[\frac{-1}{2\sigma^2_{F_{z|x,j}}}(z_j - g(x)\beta_{F_{z|x,j}})^2\right]$
- **Binary:** $P(z_j = 1|x; \theta_{F_{z|x,j}}) = \frac{\exp\left(g(x)\theta_{F_{z|x,j}}\right)}{1+\exp\left(g(x)\theta_{F_{z|x,j}}\right)}$
- **Multinomial:** $P(z_j = (k \neq K)|x; \theta_{F^k_{z|x,j}}) = \frac{\exp\left(g(x)\theta_{F^k_{z|x,j}}\right)}{1+\sum_{\ell=1}^{K-1} \exp\left(g(x)\theta_{F^\ell_{z|x,j}}\right)}$

Conclusion

A2.2: Multiyear (Diversity) Likelihood

$$\mathcal{L}_N^U(\theta) = \prod_{n=1}^{N_A} f_x(x_n;\theta_{F_x}) f_t(t_n;\theta_{F_t}) f_{z|x}(z_n|x_n;\theta_{F_{z|x}}) f_a(a) f_{\bar{a}}(\bar{a}) f_{\bar{a}|a}(\bar{a}|a) P_{d_{2,n}} P_{y_n}^{\mathbb{1}(y_n=S)} (1-P_{y_n})^{\mathbb{1}(y_n=F)}$$

$$\prod_{n=N_A+1}^{N_{T,R}} f_x(x_n;\theta_{F_x}) f_t(t_n;\theta_{F_t}) f_{z|x}(z_n|x_n;\theta_{F_{z|x}}) f_a(a) f_{\bar{a}}(\bar{a}) (1-P_{d_{2,n}}) P_{y_n}^{\mathbb{1}(y_n=S)} (1-P_{y_n})^{\mathbb{1}(y_n=F)}$$

$$\prod_{n=N_{T,R}+1}^{N} f_x(x_n;\theta_{F_x}) f_t(t_n;\theta_{F_t}) f_{z|x}(z_n|x_n;\theta_{F_{z|x}}) f_a(a) f_{\bar{a}}(\bar{a}) (1-P_{d_{1,n}})$$

- Estimate $f_{\bar{a}|a}(\bar{a}|a)$ on N_A accepted applicants only
- As with year-dynamic model, for $\mathcal{L}_R$, use (θ_F^U, θ_S^U) as initial guess of (θ_F^R, θ_S^R)

Conclusion

A3: Means by Program

Table 2a: Means by Program

	Economics	Government	History	Linguistics	Psychology
Accept	0.1121	0.0430	0.0986	0.0678	0.0535
CovidYear	0.2478	0.2792	0.3029	0.3460	0.3004
WinsorAge	26.2782	27.9633	26.8478	28.0692	25.8230
Female	0.4201	0.4182	0.4232	0.6133	0.7490
USAfrHispNat	0.0289	0.0766	0.1159	0.0665	0.1728
USAsian	0.0313	0.0421	0.0304	0.0353	0.0576
IntAsian	0.5322	0.2510	0.1058	0.2714	0.1523
IntOther	0.2517	0.2967	0.2203	0.3256	0.1584
GREVerbalPct	71.8677	81.3486	82.6054	73.5451	75.6192
GREQuantPct	86.2163	63.3428	49.3295	57.8455	58.0000
GREAnalyticPct	52.6351	72.1905	75.0460	63.6824	69.2077
UgradGPA	3.6534	3.5675	3.6531	3.6567	3.5695
TOEFL/IELTS	7.5232	7.5422	7.4252	7.5444	7.3158
EliteUSUni	0.1516	0.1847	0.2565	0.1954	0.2840
EliteUSLA	0.0423	0.0672	0.0696	0.0231	0.0535
EliteForeign	0.0717	0.0578	0.0478	0.0488	0.0206
OtherForeign	0.5736	0.3953	0.2333	0.5102	0.1852
GradDegree	0.7478	0.7553	0.6652	0.7544	0.4259
WorkExper	0.5938	0.7463	0.6638	0.7544	0.7593
#ProfRecom	2.5173	2.3469	2.6261	2.4355	2.1831
#ProlificRecom	1.0760	0.6912	0.5043	0.7069	0.3128
#MathCourses	6.6396				
AdvMath	0.4827				
MissingGRE	0.0255	0.4612	0.6217	0.6839	0.4650
MissingUgradGPA	0.6607	0.4827	0.3072	0.5726	0.2490
MissingTOEFL/IELTS	0.5958	0.7714	0.8449	0.7707	0.8827
Observations	2078	2231	690	737	486

- **Economics Highest:** Accept, IntAsian, GREQuantPct, EliteForeign, OtherForeign, #ProlificRecom, MissingUgradGPA
- **Economics Lowest:** CovidYear, USAfrHispNat, GREVerbalPct, GREAnalyticPct, EliteUSUni, WorkExper, MissingGRE, MissingTOEFL/IELTS

Reduced-Form Summary

A3: Means by Program, Accept = 1

Table 2b: Means by Program, Accept = 1

	Economics	Government	History	Linguistics	Psychology
CovidYear	0.1888	0.2188	0.2059	0.2200	0.2308
WinsorAge	25.0815	27.7292	27.2794	27.1000	25.7692
Female	0.4850	0.5000	0.5588	0.5800	0.6154
USAfrHispNat	0.0386	0.1458	0.1765	0.0400	0.0769
USAsian	0.0429	0.0312	0.0147	0.0600	0.1154
IntAsian	0.4163	0.1667	0.0882	0.3600	0.0769
IntOther	0.2575	0.2292	0.3235	0.2000	0.1538
GREVerbalPct	84.3980	88.8725	86.6328	77.9161	85.7729
GREQuantPct	91.9289	68.3708	54.8113	64.5504	62.3462
GREAnalyticPct	69.0355	82.7222	78.0879	68.8958	74.6169
UgradGPA	3.7336	3.6404	3.7204	3.7004	3.6341
TOEFL/IELTS	7.6419	7.6050	7.4730	7.6237	7.3178
EliteUSUni	0.2833	0.3125	0.3382	0.2200	0.5385
EliteUSLA	0.1030	0.1458	0.1176	0.0200	0.1154
EliteForeign	0.1030	0.0521	0.0588	0.1000	0.0385
OtherForeign	0.3863	0.2396	0.2647	0.4000	0.1154
GradDegree	0.5837	0.6771	0.7206	0.7400	0.4615
WorkExper	0.6309	0.8125	0.7647	0.7000	0.9231
#ProfRecom	2.5494	2.3750	2.8235	2.7200	2.2308
#ProlificRecom	1.2833	0.9167	0.6765	1.0800	0.4615
#MathCourses	7.2575				
AdvMath	0.6781				
MissingGRE	0.0086	0.2917	0.6324	0.5800	0.1923
MissingUgradGPA	0.4893	0.3125	0.3088	0.4800	0.1923
MissingTOEFL/IELTS	0.6567	0.8854	0.8529	0.7600	0.8846
Observations	233	96	68	50	26

- **Economics Highest:** IntAsian, GREQuantPct, UGradGPA, TOEFL/IELTS, EliteForeign, #ProlificRecom, MissingUgradGPA
- **Economics Lowest:** CovidYear, WinsorAge, Female, USAfrHispNat, WorkExper, MissingGRE, MissingTOEFL/IELTS

Reduced-Form Summary

A3: Correlation Matrix

Table 3: Correlation Matrix

	Covid	Age	Fem	USAHN	USAsn	IntAsn	IntOth	GREV	GREQ	GREA	GPA	T/I	EUSUni	EUSLA	EFor	OthFor	Grad	Work	Prof	Pro	MGRE	MGPA	MT/I
CovidYear	1.00																						
WinsorAge	0.01	1.00																					
Female	0.02	-0.13	1.00																				
USAfrHispNat	0.00	-0.04	0.04	1.00																			
USAsian	-0.00	-0.06	0.05	-0.05	1.00																		
IntAsian	-0.05	-0.07	0.02	-0.19	-0.14	1.00																	
IntOther	0.01	0.18	-0.06	-0.17	-0.12	-0.42	1.00																
GREVerbalPct	0.03	-0.06	-0.04	0.00	0.04	-0.12	-0.15	1.00															
GREQuantPct	-0.02	-0.16	-0.10	-0.18	0.00	0.44	-0.10	0.16	1.00														
GREAnalyticPct	0.05	-0.06	0.03	0.08	0.08	-0.37	-0.08	0.60	-0.20	1.00													
UgradGPA	-0.02	-0.29	0.07	-0.13	-0.02	0.02	0.00	0.06	0.12	0.05	1.00												
TOEFL/IELTS	-0.01	-0.07	0.01	-0.02	0.01	0.04	0.00	0.24	0.12	0.19	0.00	1.00											
EliteUSUni	0.01	-0.12	0.02	0.12	0.14	-0.12	-0.22	0.16	-0.00	0.19	-0.01	-0.02	1.00										
EliteUSLA	-0.02	-0.02	0.04	0.04	0.04	-0.08	-0.09	0.12	-0.01	0.13	-0.02	-0.00	-0.11	1.00									
EliteForeign	-0.00	-0.04	-0.00	-0.06	-0.04	0.09	0.09	0.02	0.08	-0.02	0.01	0.04	-0.12	-0.06	1.00								
OtherForeign	-0.02	0.20	-0.04	-0.23	-0.14	0.34	0.39	-0.26	0.20	-0.39	0.02	0.02	-0.43	-0.21	-0.22	1.00							
GradDegree	0.00	0.41	-0.08	-0.13	-0.09	0.21	0.15	-0.14	0.05	-0.20	-0.22	0.03	-0.21	-0.10	0.05	0.37	1.00						
WorkExper	0.01	0.33	0.05	0.05	0.01	-0.18	0.11	0.01	-0.15	0.11	-0.08	-0.03	-0.02	0.03	-0.03	-0.01	0.10	1.00					
#ProfRecom	-0.02	-0.19	-0.04	-0.04	0.01	0.11	-0.09	0.01	0.09	-0.04	0.14	0.03	-0.02	0.02	-0.00	-0.02	-0.03	-0.18	1.00				
#ProlificRecom	0.01	-0.06	-0.02	-0.07	-0.01	0.24	-0.10	-0.01	0.25	-0.11	0.04	0.10	-0.01	-0.01	0.06	0.08	0.17	-0.09	0.19	1.00			
MissingGRE	0.09	0.15	0.05	0.11	-0.01	-0.22	0.17	0.09	-0.33	0.17	-0.09	-0.10	-0.03	-0.04	-0.03	-0.01	0.02	0.10	-0.08	-0.20	1.00		
MissingUgradGPA	-0.01	0.18	-0.04	-0.24	-0.15	0.36	0.42	-0.24	0.21	-0.38	0.02	0.04	-0.46	-0.23	0.23	0.83	0.37	-0.02	-0.03	0.10	-0.01	1.00	
MissingTOEFL/IELTS	0.05	-0.07	0.03	0.16	0.11	-0.32	-0.22	0.16	-0.24	0.32	-0.02	-0.02	0.29	0.14	-0.04	-0.58	-0.20	0.05	-0.07	-0.05	0.12	-0.58	1.00
Observations	6222																						

Reduced-Form Summary

A3: Logistic Regression Results

Table 4a: Logistic Regression Results

DV = Accept	(1) Economics	(2) Government	(3) History	(4) Linguistics	(5) Psychology
CovidYear	-0.3966**	-0.4332*	-0.5752*	-0.5501	-0.1766
	(0.2010)	(0.2612)	(0.3479)	(0.4129)	(0.5545)
WinsorAge	-0.0995***	0.0454*	0.0380	0.0222	-0.0520
	(0.0358)	(0.0271)	(0.0327)	(0.0532)	(0.0899)
Female	0.4079**	0.6723***	0.6539**	0.1311	-0.5060
	(0.1681)	(0.2299)	(0.2971)	(0.3452)	(0.5606)
USAfrHispNat	0.4221	1.0081***	1.1601***	0.0120	-0.8263
	(0.5258)	(0.3545)	(0.4426)	(0.8411)	(1.1611)
USAsian	-0.5394	-0.5669	-0.3260	0.8638	1.1711
	(0.4199)	(0.6504)	(1.2512)	(0.7201)	(0.7276)
IntAsian	-0.8445***	-0.1853	0.9405	0.4890	-0.7827
	(0.2945)	(0.4146)	(0.7233)	(0.6729)	(0.9323)
IntOther	0.5034	0.3781	1.3523***	-0.1061	0.6239
	(0.3172)	(0.4131)	(0.5086)	(0.7483)	(1.1070)
GREVerbalPct	0.0155***	0.0281*	0.0753**	-0.0092	0.0607***
	(0.0060)	(0.0160)	(0.0344)	(0.0154)	(0.0218)
GREQuantPct	0.1547***	0.0161*	0.0210*	0.0211	-0.0138
	(0.0186)	(0.0086)	(0.0116)	(0.0150)	(0.0159)
GREAnalyticPct	0.0179***	0.0199**	0.0030	0.0175	-0.0202
	(0.0042)	(0.0094)	(0.0134)	(0.0127)	(0.0218)
UgradGPA	2.2212***	0.6968	1.3648**	1.2645	1.7772*
	(0.7219)	(0.5476)	(0.5513)	(0.9703)	(0.9487)
TOEFL/IELTS	0.3878	0.6456	1.0963**	0.9655*	-0.4656
	(0.2883)	(0.4708)	(0.5526)	(0.5456)	(0.6112)
EliteUSUni	0.8850***	0.3943	0.6541*	-0.6057	1.4303**
	(0.2960)	(0.3135)	(0.3802)	(0.4985)	(0.6192)
EliteUSLA	1.1173***	0.6276*	1.0698**	-0.6088	2.3151**
	(0.3813)	(0.3754)	(0.5399)	(1.4186)	(1.0642)
EliteForeign	1.0061*	0.4759	1.7715**	1.6195*	0.3889
	(0.6060)	(0.8224)	(0.7938)	(0.8587)	(1.9889)
OtherForeign	0.5442	0.5777	1.3733**	0.4188	-1.0737
	(0.5765)	(0.7686)	(0.6992)	(0.7157)	(1.3016)
GradDegree	0.0467	0.0733	0.3128	0.4049	0.4892
	(0.2238)	(0.2583)	(0.3280)	(0.4896)	(0.6399)
WorkExper	0.3932**	0.4027	0.4972	0.1495	1.8201**
	(0.1889)	(0.2993)	(0.3295)	(0.3778)	(0.8564)
#ProfRecom	0.0340	-0.0179	0.5511**	0.4781*	-0.0981
	(0.1317)	(0.1339)	(0.2554)	(0.2662)	(0.2660)
#ProlificRecom	0.2635***	0.3025**	0.1880	0.3284**	0.5901*
	(0.0854)	(0.1262)	(0.1576)	(0.1544)	(0.3145)
#MathCourses	0.1689***				
	(0.0596)				
AdvMath	0.2319				
	(0.1790)				
MissingGRE	0.1899	-0.3259	0.6282	-0.0831	-1.1514**
	(0.7646)	(0.3100)	(0.4275)	(0.3761)	(0.5702)
MissingUgradGPA	-0.4745	-0.4917	-1.5492**	-1.1097*	0.4690
	(0.4891)	(0.5440)	(0.6893)	(0.6481)	(1.1831)
MissingTOEFL/IELTS	-0.3786	0.6188	0.6745	-0.0440	-1.7224*
	(0.2432)	(0.5657)	(0.5190)	(0.5099)	(0.9271)
Concentration FEs	No	Yes	Yes	Yes	Yes
Observations	2078	2231	690	737	486
Pseudo-R^2	0.2677	0.1525	0.1982	0.1871	0.2475
CV Pseudo-R^2	0.2102	0.0720	0.0604	-0.0265	-0.2787

Robust standard errors in parentheses: *p<0.10, **p<0.05, ***p<0.01.

- **Economics Positive ($p < .05$):** Female, GREVerbalPct, GREQuantPct, GREAnalyticPct, UgradGPA, EliteUSUni, EliteUSLA, WorkExper, #ProlificRecom, #MathCourses
- **Economics Negative ($p < .05$):** CovidYear, WinsorAge, IntAsian

Post-Lasso Logistic Regression AMEs

A3: Logistic Regression AMEs

Table 4b: Logistic Regression AMEs

DV = Accept	(1) Economics	(2) Government	(3) History	(4) Linguistics	(5) Psychology	(6) Non-Economics
CovidYear	-0.0303**	-0.0164	-0.0431*	-0.0298	-0.0075	-0.0218***
	(0.0153)	(0.0100)	(0.0261)	(0.0224)	(0.0238)	(0.0084)
WinsorAge	-0.0076***	0.0017*	0.0028	0.0012	-0.0022	0.0016*
	(0.0027)	(0.0010)	(0.0025)	(0.0029)	(0.0038)	(0.0009)
Female	0.0312**	0.0254***	0.0490**	0.0071	-0.0216	0.0207***
	(0.0129)	(0.0088)	(0.0220)	(0.0187)	(0.0239)	(0.0075)
USAfrHispNat	0.0323	0.0381***	0.0869***	0.0007	-0.0352	0.0384***
	(0.0402)	(0.0137)	(0.0332)	(0.0455)	(0.0487)	(0.0119)
USAsian	-0.0413	-0.0215	-0.0244	0.0468	0.0499	0.0062
	(0.0322)	(0.0247)	(0.0936)	(0.0391)	(0.0313)	(0.0185)
IntAsian	-0.0646***	-0.0070	0.0704	0.0265	-0.0334	0.0069
	(0.0224)	(0.0157)	(0.0543)	(0.0363)	(0.0393)	(0.0132)
IntOther	0.0385	0.0143	0.1013***	-0.0057	0.0266	0.0238*
	(0.0243)	(0.0157)	(0.0385)	(0.0406)	(0.0471)	(0.0132)
GREVerbalPct	0.0012***	0.0011*	0.0056**	-0.0005	0.0026***	0.0015***
	(0.0005)	(0.0006)	(0.0026)	(0.0008)	(0.0010)	(0.0005)
GREQuantPct	0.0118***	0.0006*	0.0016*	0.0011	-0.0006	0.0006**
	(0.0014)	(0.0003)	(0.0009)	(0.0008)	(0.0007)	(0.0003)
GREAnalyticPct	0.0014***	0.0008**	0.0002	0.0009	-0.0009	0.0007**
	(0.0003)	(0.0004)	(0.0010)	(0.0007)	(0.0009)	(0.0003)
UgradGPA	0.1699***	0.0264	0.1022**	0.0684	0.0757*	0.0488***
	(0.0551)	(0.0208)	(0.0423)	(0.0522)	(0.0418)	(0.0176)
TOEFL/IELTS	0.0297	0.0244	0.0821**	0.0523*	-0.0198	0.0326***
	(0.0219)	(0.0179)	(0.0417)	(0.0301)	(0.0259)	(0.0123)
EliteUSUni	0.0677***	0.0149	0.0490*	-0.0328	0.0610**	0.0233**
	(0.0225)	(0.0119)	(0.0281)	(0.0264)	(0.0271)	(0.0098)
EliteUSLA	0.0855***	0.0238*	0.0801**	-0.0330	0.0987**	0.0420***
	(0.0288)	(0.0143)	(0.0402)	(0.0761)	(0.0480)	(0.0136)
EliteForeign	0.0770*	0.0180	0.1327**	0.0877*	0.0166	0.0479**
	(0.0463)	(0.0311)	(0.0591)	(0.0481)	(0.0850)	(0.0241)
OtherForeign	0.0416	0.0219	0.1028*	0.0227	-0.0458	0.0273
	(0.0441)	(0.0291)	(0.0527)	(0.0391)	(0.0556)	(0.0221)
GradDegree	0.0036	0.0028	0.0234	0.0219	0.0208	0.0106
	(0.0171)	(0.0098)	(0.0247)	(0.0262)	(0.0273)	(0.0089)
WorkExper	0.0301**	0.0152	0.0372	0.0081	0.0776**	0.0221**
	(0.0144)	(0.0113)	(0.0248)	(0.0205)	(0.0368)	(0.0089)
#ProfRecom	0.0026	-0.0007	0.0413**	0.0259*	-0.0042	0.0063
	(0.0101)	(0.0051)	(0.0190)	(0.0142)	(0.0113)	(0.0047)
#ProlificRecom	0.0202***	0.0114**	0.0141	0.0178**	0.0251*	0.0133***
	(0.0065)	(0.0048)	(0.0118)	(0.0082)	(0.0130)	(0.0038)
#MathCourses	0.0129***					
	(0.0045)					
AdvMath	0.0177					
	(0.0137)					
MissingGRE	0.0145	-0.0123	0.0470	-0.0045	-0.0491*	-0.0062
	(0.0585)	(0.0118)	(0.0319)	(0.0204)	(0.0252)	(0.0088)
MissingUgradGPA	-0.0363	-0.0186	-0.1160**	-0.0601*	0.0200	-0.0291
	(0.0375)	(0.0206)	(0.0524)	(0.0355)	(0.0505)	(0.0179)
MissingTOEFL/IELTS	-0.0290	0.0234	0.0505	-0.0024	-0.0734*	0.0108
	(0.0188)	(0.0215)	(0.0388)	(0.0276)	(0.0417)	(0.0135)
Concentration FEs	No	Yes	Yes	Yes	Yes	Yes
Observations	2078	2231	690	737	486	4144
Wald Stat | DF | P-Val	115.8837	23	0.0000			

Robust standard errors in parentheses: *p<0.10, **p<0.05, ***p<0.01.

- **Economics Positive ($p < .05$):** Female, GREVerbalPct, GREQuantPct, GREAnalyticPct, UgradGPA, EliteUSUni, EliteUSLA, WorkExper, #ProlificRecom, #MathCourses
- **Economics Negative ($p < .05$):** CovidYear, WinsorAge, IntAsian

Post-Lasso Logistic Regression AMEs

A3: Logistic Regression Results (Synthetic)

Table 5a: Logistic Regression Results (Synthetic)

DV = Accept	(1) Economics	(2) Government	(3) History	(4) Linguistics	(5) Psychology
CovidYear	-0.1997	-0.0323	0.2028	-0.4791	-0.5946
	(0.1633)	(0.2215)	(0.3078)	(0.3477)	(0.4520)
WinsorAge	-0.0509**	-0.0198	0.0576*	-0.0164	0.1203***
	(0.0201)	(0.0174)	(0.0307)	(0.0357)	(0.0400)
Female	0.1941	0.0923	0.1389	0.2595	0.2119
	(0.1402)	(0.2004)	(0.2526)	(0.3255)	(0.4310)
USAfrHispNat	0.3053	-0.1457	-0.2379	-1.6401	0.5413
	(0.3724)	(0.4303)	(0.4670)	(1.0720)	(0.5306)
USAsian	0.5663	0.6016	-0.7934	-0.4305	0.7122
	(0.3642)	(0.4452)	(1.1675)	(0.7936)	(0.8863)
IntAsian	-0.1428	0.1630	0.5780	-0.4965	0.1868
	(0.2169)	(0.2803)	(0.3740)	(0.4275)	(0.6866)
IntOther	-0.1231	0.1395	0.1097	-0.1602	-1.0807
	(0.2311)	(0.3046)	(0.3237)	(0.3832)	(0.7583)
GREVerbalPct	0.0167***	0.0247**	0.0164	-0.0029	0.0132
	(0.0048)	(0.0117)	(0.0127)	(0.0100)	(0.0184)
GREQuantPct	0.0233***	-0.0027	0.0026	0.0304**	0.0097
	(0.0090)	(0.0051)	(0.0088)	(0.0137)	(0.0099)
GREAnalyticPct	0.0042	0.0004	-0.0073	-0.0042	0.0069
	(0.0031)	(0.0059)	(0.0092)	(0.0101)	(0.0103)
UgradGPA	0.2292	0.6327	1.3552**	-1.3171**	-0.1002
	(0.4745)	(0.4985)	(0.5796)	(0.5584)	(0.6152)
TOEFL/IELTS	-0.4673**	0.5141	-0.7648	0.2446	-0.7354
	(0.2157)	(0.4185)	(0.6814)	(0.7498)	(0.8025)
EliteUSUni	-0.4850*	-0.2243	0.0572	0.4764	0.3941
	(0.2560)	(0.3258)	(0.3421)	(0.4788)	(0.4782)
EliteUSLA	0.2429	0.1759	0.2358	0.4860	0.8652
	(0.3049)	(0.4042)	(0.4964)	(0.9631)	(0.7261)
EliteForeign	-0.1622	-1.1929	0.7404	0.4801	3.0530***
	(0.3015)	(0.7484)	(0.5668)	(0.7841)	(0.8673)
OtherForeign	-0.1087	0.2043	0.2721	0.1731	0.3023
	(0.1979)	(0.2732)	(0.3391)	(0.4292)	(0.5926)
GradDegree	-0.0198	0.1770	-0.1601	-0.8698***	-0.2769
	(0.1624)	(0.2439)	(0.2765)	(0.3320)	(0.3814)
WorkExper	0.2525*	-0.0391	-0.0736	-0.2650	-1.1936**
	(0.1441)	(0.2396)	(0.2629)	(0.3417)	(0.4805)
#ProfRecom	-0.1059	0.0911	-0.1828	0.2181	-0.4923**
	(0.0909)	(0.1138)	(0.1473)	(0.1817)	(0.1956)
#ProlificRecom	0.0039	0.2189**	-0.1743	0.0673	0.5134**
	(0.0656)	(0.1108)	(0.1723)	(0.1642)	(0.2213)
#MathCourses	0.0366				
	(0.0421)				
AdvMath	0.1961				
	(0.1416)				
MissingGRE	-0.1993	-0.2029	-0.0011	-0.0433	-0.6040
	(0.4328)	(0.2195)	(0.2689)	(0.3503)	(0.4017)
MissingUgradGPA	0.1531	0.0895	-0.2455	0.6298**	-0.3574
	(0.1548)	(0.2291)	(0.3015)	(0.3125)	(0.4342)
MissingTOEFL/IELTS	-0.2950*	0.4898	0.5752	0.1346	-2.0781***
	(0.1640)	(0.3480)	(0.5466)	(0.4345)	(0.7633)
Concentration FEs	No	Yes	Yes	Yes	Yes
Observations	2078	2231	690	737	486
Pseudo-R^2	0.0524	0.0366	0.0753	0.1046	0.2230
CV Pseudo-R^2	0.0139	-0.0189	-0.0887	0.0055	-0.0014

Robust standard errors in parentheses: *p<0.10, **p<0.05, ***p<0.01.

- **Economics Positive ($p < .05$):** GREVerbalPct, GREQuantPct
- **Economics Negative ($p < .05$):** WinsorAge, TOEFL/IELTS

▶▶ Post-Lasso Logistic Regression AMEs

A3: Logistic Regression AMEs (Synthetic)

Table 5b: Logistic Regression AMEs (Synthetic)

DV = Accept	(1) Economics	(2) Government	(3) History	(4) Linguistics	(5) Psychology	(6) Non-Economics
CovidYear	-0.0204	-0.0014	0.0192	-0.0298	-0.0345	-0.0089
	(0.0167)	(0.0099)	(0.0291)	(0.0216)	(0.0262)	(0.0086)
WinsorAge	-0.0052**	-0.0009	0.0054*	-0.0010	0.0070***	0.0004
	(0.0021)	(0.0008)	(0.0029)	(0.0022)	(0.0023)	(0.0008)
Female	0.0198	0.0041	0.0131	0.0162	0.0123	0.0099
	(0.0143)	(0.0089)	(0.0239)	(0.0204)	(0.0251)	(0.0078)
USAfrHispNat	0.0312	-0.0065	-0.0225	-0.1021	0.0314	-0.0137
	(0.0381)	(0.0192)	(0.0441)	(0.0673)	(0.0306)	(0.0147)
USAsian	0.0579	0.0268	-0.0750	-0.0268	0.0413	0.0241
	(0.0372)	(0.0199)	(0.1101)	(0.0495)	(0.0516)	(0.0179)
IntAsian	-0.0146	0.0073	0.0546	-0.0309	0.0108	0.0075
	(0.0222)	(0.0125)	(0.0353)	(0.0263)	(0.0399)	(0.0112)
IntOther	-0.0126	0.0062	0.0104	-0.0100	-0.0627	-0.0014
	(0.0236)	(0.0136)	(0.0306)	(0.0237)	(0.0443)	(0.0106)
GREVerbalPct	0.0017***	0.0011**	0.0015	-0.0002	0.0008	0.0008**
	(0.0005)	(0.0005)	(0.0012)	(0.0006)	(0.0010)	(0.0004)
GREQuantPct	0.0024***	-0.0001	0.0003	0.0019**	0.0006	0.0003
	(0.0009)	(0.0002)	(0.0008)	(0.0009)	(0.0006)	(0.0002)
GREAnalyticPct	0.0004	0.0000	-0.0007	-0.0003	0.0004	0.0000
	(0.0003)	(0.0003)	(0.0009)	(0.0006)	(0.0006)	(0.0002)
UgradGPA	0.0234	0.0282	0.1281**	-0.0820**	-0.0058	0.0130
	(0.0485)	(0.0223)	(0.0553)	(0.0358)	(0.0357)	(0.0158)
TOEFL/IELTS	-0.0478**	0.0229	-0.0723	0.0152	-0.0427	0.0050
	(0.0221)	(0.0187)	(0.0645)	(0.0466)	(0.0469)	(0.0187)
EliteUSUni	-0.0496*	-0.0100	0.0054	0.0297	0.0229	0.0036
	(0.0261)	(0.0145)	(0.0324)	(0.0297)	(0.0274)	(0.0108)
EliteUSLA	0.0248	0.0078	0.0223	0.0303	0.0502	0.0217
	(0.0312)	(0.0180)	(0.0469)	(0.0602)	(0.0418)	(0.0160)
EliteForeign	-0.0166	-0.0532	0.0700	0.0299	0.1771***	0.0158
	(0.0308)	(0.0337)	(0.0537)	(0.0490)	(0.0484)	(0.0179)
OtherForeign	-0.0111	0.0091	0.0257	0.0108	0.0175	0.0116
	(0.0202)	(0.0122)	(0.0321)	(0.0267)	(0.0344)	(0.0103)
GradDegree	-0.0020	0.0079	-0.0151	-0.0542***	-0.0161	-0.0093
	(0.0166)	(0.0109)	(0.0261)	(0.0206)	(0.0220)	(0.0085)
WorkExper	0.0258*	-0.0017	-0.0070	-0.0165	-0.0692**	-0.0093
	(0.0148)	(0.0107)	(0.0248)	(0.0213)	(0.0275)	(0.0086)
#ProfRecom	-0.0108	0.0041	-0.0173	0.0136	-0.0286***	-0.0027
	(0.0093)	(0.0051)	(0.0140)	(0.0114)	(0.0110)	(0.0042)
#ProlificRecom	0.0004	0.0098*	-0.0165	0.0042	0.0298**	0.0083*
	(0.0067)	(0.0050)	(0.0164)	(0.0102)	(0.0128)	(0.0045)
#MathCourses	0.0037					
	(0.0043)					
AdvMath	0.0201					
	(0.0145)					
MissingGRE	-0.0204	-0.0090	-0.0001	-0.0027	-0.0350	-0.0098
	(0.0443)	(0.0098)	(0.0254)	(0.0218)	(0.0239)	(0.0079)
MissingUgradGPA	0.0157	0.0040	-0.0232	0.0392*	-0.0207	0.0019
	(0.0158)	(0.0102)	(0.0285)	(0.0201)	(0.0254)	(0.0083)
MissingTOEFL/IELTS	-0.0302*	0.0218	0.0544	0.0084	-0.1205***	0.0063
	(0.0168)	(0.0156)	(0.0517)	(0.0272)	(0.0434)	(0.0130)
Concentration FEs	No	Yes	Yes	Yes	Yes	Yes
Observations	2078	2231	690	737	486	4144
Wald Stat | DF | P-Val	37.4760	23	0.0290			

Robust standard errors in parentheses: *p<0.10, **p<0.05, ***p<0.01.

- **Economics Positive ($p < .05$):** GREVerbalPct, GREQuantPct
- **Economics Negative ($p < .05$):** WinsorAge, TOEFL/IELTS

▸▸ Post-Lasso Logistic Regression AMEs

A3: Lasso Logistic Regression Results

Table 6: Lasso Logistic Regression Results

DV = Accept	(1) Economics	(2) Government	(3) History	(4) Linguistics	(5) Psychology
CovidYear	-0.3330	-0.3123	-0.3498	-0.2378	
WinsorAge	-0.0788	0.0266	0.0200		
Female	0.3352	0.5096	0.5068		-0.0654
USAfrHispNat	0.2638	0.8041	0.7157		
USAsian	-0.2802	-0.2918		0.0413	0.1155
IntAsian	-0.6744	-0.0726		0.0465	
IntOther	0.4729	0.1946	0.7240	-0.1087	
GREVerbalPct	0.0139	0.0252	0.0272		0.0343
GREQuantPct	0.1349	0.0119	0.0187	0.0154	
GREAnalyticPct	0.0166	0.0208		0.0080	
UgradGPA	1.9977	0.4621	0.7414	0.1714	
TOEFL/IELTS	0.4009	0.3295	0.5199	0.5151	
EliteUSUni	0.6886	0.2709	0.3267		0.4606
EliteUSLA	0.8956	0.5199	0.5985		0.4470
EliteForeign	0.3724		0.0414	0.4343	
OtherForeign					
GradDegree			0.0978		
WorkExper	0.2835	0.3447	0.3273		0.5559
#ProfRecom			0.3739	0.2322	
#ProlificRecom	0.2243	0.2362	0.1651	0.2213	0.0632
#MathCourses	0.1493				
AdvMath	0.2272				
MissingGRE		-0.2304		-0.0527	-0.5416
MissingUgradGPA					
MissingTOEFL/IELTS	-0.2364	0.2852	0.0796		
Concentration FEs	No	Yes	Yes	Yes	Yes
Observations	2078	2231	690	737	486
Pseudo-R^2	0.2642	0.1456	0.1589	0.1486	0.1362
CV Pseudo-R^2	0.2297	0.0912	0.0592	0.0850	0.0537

Post-Lasso Logistic Regression AMEs

A3: Full Post-Lasso Logistic Regression Results

Table 7a: Post-Lasso Logistic Regression Results

DV = Accept	(1) Economics	(2) Government	(3) History	(4) Linguistics	(5) Psychology
CovidYear	-0.3960**	-0.4191	-0.5330	-0.5737	
	(0.1996)	(0.2609)	(0.3435)	(0.3824)	
WinsorAge	-0.0977***	0.0473*	0.0440		
	(0.0333)	(0.0248)	(0.0325)		
Female	0.4106**	0.6570***	0.6797**		-0.3204
	(0.1670)	(0.2281)	(0.2932)		(0.4908)
USAfrHispNat	0.4355	0.9687***	1.1594***		
	(0.5232)	(0.3521)	(0.4187)		
USAsian	-0.5139	-0.5533		0.6970	0.7934
	(0.4149)	(0.6435)		(0.6906)	(0.6164)
IntAsian	-0.7960***	-0.0979		0.3796	
	(0.2665)	(0.3808)		(0.4458)	
IntOther	0.5490*	0.3749	1.1102**	-0.2036	
	(0.2838)	(0.3238)	(0.4378)	(0.4436)	
GREVerbalPct	0.0155***	0.0335*	0.0423**		0.0498***
	(0.0059)	(0.0180)	(0.0188)		(0.0185)
GREQuantPct	0.1549***	0.0156*	0.0255**	0.0157	
	(0.0184)	(0.0091)	(0.0106)	(0.0120)	
GREAnalyticPct	0.0177***	0.0232**		0.0159	
	(0.0041)	(0.0101)		(0.0121)	
UgradGPA	2.2336***	0.7028	1.3004**	0.9096	
	(0.6626)	(0.5465)	(0.5090)	(0.9856)	
TOEFL/IELTS	0.3900	0.6701	1.0010*	0.8625*	
	(0.2878)	(0.4545)	(0.5503)	(0.5186)	
EliteUSUni	0.8292***	0.3801	0.5964*		0.7688
	(0.2312)	(0.2728)	(0.3491)		(0.4721)
EliteUSLA	1.0523***	0.6501*	1.0178**		1.3415
	(0.3373)	(0.3553)	(0.5124)		(0.8540)
EliteForeign	0.4772*		0.5710	0.9748	
	(0.2702)		(0.5770)	(0.5963)	
GradDegree			0.2774		
			(0.3193)		
WorkExper	0.3826**	0.4139	0.5055		1.6031**
	(0.1881)	(0.2987)	(0.3290)		(0.6992)
#ProfRecom			0.5752**	0.4712*	
			(0.2597)	(0.2697)	
#ProlificRecom	0.2727***	0.3028**	0.2113	0.3359**	0.4341
	(0.0840)	(0.1229)	(0.1577)	(0.1456)	(0.2885)
#MathCourses	0.1715***				
	(0.0593)				
AdvMath	0.2350				
	(0.1777)				
MissingGRE	0.1827			-0.0909	-0.8985
	(0.7660)			(0.3941)	(0.5569)
MissingTOEFL/IELTS	-0.3983*	0.5313	0.5689		
	(0.2266)	(0.4700)	(0.5289)		
Concentration FEs	No	Yes	Yes	Yes	Yes
Observations	2078	2231	690	737	486
Pseudo-R^2	0.2671	0.1500	0.1847	0.1722	0.1844
CV Pseudo-R^2	0.2168	0.0865	0.0715	0.0104	0.0445

Robust standard errors in parentheses: *p<0.10, **p<0.05, ***p<0.01.

- **Economics Positive ($p < .05$):** Female, GREVerbalPct, GREQuantPct, GREAnalyticPct, UgradGPA, EliteUSUni, EliteUSLA, WorkExper, #ProlificRecom, #MathCourses
- **Economics Negative ($p < .05$):** CovidYear, WinsorAge, IntAsian

Post-Lasso Logistic Regression AMEs

A3: Full Post-Lasso Logistic Regression AMEs

Table 7b: Post-Lasso Logistic Regression AMEs

DV = Accept	(1) Economics	(2) Government	(3) History	(4) Linguistics	(5) Psychology
CovidYear	-0.0303**	-0.0159	-0.0404	-0.0315	
	(0.0152)	(0.0100)	(0.0261)	(0.0212)	
WinsorAge	-0.0075***	0.0018*	0.0033		
	(0.0025)	(0.0010)	(0.0025)		
Female	0.0314**	0.0249***	0.0515**		-0.0144
	(0.0128)	(0.0087)	(0.0220)		(0.0222)
USAfrHispNat	0.0333	0.0367***	0.0878***		
	(0.0400)	(0.0136)	(0.0318)		
USAsian	-0.0394	-0.0210		0.0383	0.0357
	(0.0318)	(0.0245)		(0.0382)	(0.0270)
IntAsian	-0.0610***	-0.0037		0.0208	
	(0.0203)	(0.0144)		(0.0245)	
IntOther	0.0420*	0.0142	0.0841**	-0.0112	
	(0.0217)	(0.0123)	(0.0333)	(0.0245)	
GREVerbalPct	0.0012***	0.0013*	0.0032**		0.0022**
	(0.0005)	(0.0007)	(0.0015)		(0.0009)
GREQuantPct	0.0119***	0.0006*	0.0019**	0.0009	
	(0.0014)	(0.0004)	(0.0008)	(0.0007)	
GREAnalyticPct	0.0014***	0.0009**		0.0009	
	(0.0003)	(0.0004)		(0.0007)	
UgradGPA	0.1710***	0.0267	0.0985**	0.0499	
	(0.0506)	(0.0208)	(0.0397)	(0.0542)	
TOEFL/IELTS	0.0299	0.0254	0.0758*	0.0474	
	(0.0219)	(0.0173)	(0.0420)	(0.0290)	
EliteUSUni	0.0635***	0.0144	0.0452*		0.0346
	(0.0176)	(0.0104)	(0.0262)		(0.0214)
EliteUSLA	0.0806***	0.0247*	0.0771**		0.0604
	(0.0255)	(0.0136)	(0.0387)		(0.0398)
EliteForeign	0.0365*		0.0432	0.0535	
	(0.0207)		(0.0434)	(0.0331)	
GradDegree			0.0210		
			(0.0243)		
WorkExper	0.0293**	0.0157	0.0383		0.0722**
	(0.0143)	(0.0113)	(0.0250)		(0.0335)
#ProfRecom			0.0436**	0.0259*	
			(0.0195)	(0.0147)	
#ProlificRecom	0.0209***	0.0115**	0.0160	0.0184**	0.0195
	(0.0064)	(0.0047)	(0.0119)	(0.0080)	(0.0127)
#MathCourses	0.0131***				
	(0.0045)				
AdvMath	0.0180				
	(0.0136)				
MissingGRE	0.0140			-0.0050	-0.0404
	(0.0587)			(0.0216)	(0.0253)
MissingTOEFL/IELTS	-0.0305*	0.0202	0.0431		
	(0.0175)	(0.0179)	(0.0399)		
Concentration FEs	No	Yes	Yes	Yes	Yes
Observations	2078	2231	690	737	486

Robust standard errors in parentheses: *p<0.10, **p<0.05, ***p<0.01.

- **Economics Positive ($p < .05$):** Female, GREVerbalPct, GREQuantPct, GREAnalyticPct, UgradGPA, EliteUSUni, EliteUSLA, WorkExper, #ProlificRecom, #MathCourses
- **Economics Negative ($p < .05$):** CovidYear, WinsorAge, IntAsian

⏩ Post-Lasso Logistic Regression AMEs

A3: Elastic-Net Logistic Regression Results

Table 8: Elastic-Net Logistic Regression Results

DV = Accept	(1) Economics	(2) Government	(3) History	(4) Linguistics	(5) Psychology
CovidYear	-0.3323	-0.3013	-0.3652	-0.2642	-0.0428
WinsorAge	-0.0786	0.0231	0.0235		
Female	0.3316	0.4214	0.4373		-0.2716
USAfrHispNat	0.2622	0.7009	0.6038		-0.2580
USAsian	-0.2741	-0.4137	-0.3622	0.1731	0.4670
IntAsian	-0.6634	-0.1850	0.1309	0.1086	-0.2639
IntOther	0.4732	0.1832	0.5739	-0.1280	0.0824
GREVerbalPct	0.0140	0.0187	0.0188		0.0236
GREQuantPct	0.1324	0.0117	0.0166	0.0136	
GREAnalyticPct	0.0165	0.0157	0.0055	0.0089	
UgradGPA	1.9971	0.5294	0.7165	0.3104	0.3833
TOEFL/IELTS	0.4029	0.4179	0.6717	0.5298	
EliteUSUni	0.6894	0.3109	0.3740		0.5669
EliteUSLA	0.8906	0.5376	0.6277		0.7887
EliteForeign	0.3738	0.0332	0.3675	0.5020	0.3558
OtherForeign		0.0233	0.1382		
GradDegree		0.0315	0.1873		0.1018
WorkExper	0.2822	0.3230	0.3192		0.5851
#ProfRecom		-0.0179	0.3250	0.2333	
#ProlificRecom	0.2238	0.2164	0.1665	0.2212	0.1970
#MathCourses	0.1489				
AdvMath	0.2309				
MissingGRE		-0.3089	0.1123	-0.0864	-0.5616
MissingUgradGPA		-0.1040	-0.1046		
MissingTOEFL/IELTS	-0.2369	0.2950	0.2603		-0.1782
Concentration FEs	No	Yes	Yes	Yes	Yes
Observations	2078	2231	690	737	486
Pseudo-R^2	0.2640	0.1422	0.1626	0.1519	0.1653
CV Pseudo-R^2	0.2297	0.0999	0.0786	0.0859	0.0582
α^*	0.9	0.0	0.0	0.4	0.1

Post-Lasso Logistic Regression AMEs

A3: Economics Means (Matriculation)

Table 9: Economics Means (Matriculation)

Mean	All Observations	Matriculate = 1
Matriculate	0.2814	
CovidYear	0.1905	0.2000
WinsorAge	25.0303	25.1692
Female	0.4848	0.4154
International	0.6710	0.7385
GREVerbalPct	84.5065	79.7385
GREQuantPct	91.9784	91.2308
GREAnalyticPct	69.1775	65.4615
UgradGPA	3.7160	3.6868
TOEFL/IELTS	7.6394	7.5953
EliteUgrad	0.4892	0.4000
GradDegree	0.5801	0.6308
WorkExper	0.6320	0.5231
#ProfRecom	2.5498	2.5846
#ProlificRecom	1.2727	1.1692
AdvMath	0.6753	0.5077
MissingUgradGPA	0.4892	0.5077
MissingTOEFL/IELTS	0.6537	0.6000
Observations	231	65

Reduced-Form Summary

Table 10: Correlation Matrix (Matriculation)

	Covid	Age	Fem	USAHN	USAsn	IntAsn	IntOth	GREV	GREQ	GREA	GPA	T/I	EUSUni	EUSLA	EFor	OthFor	Grad	Work	Prof	Pro	MGRE	MGPA	MT/I
CovidYear	1.00																						
WinsorAge	0.01	1.00																					
Female	0.02	-0.13	1.00																				
USAfrHispNat	0.00	-0.04	0.04	1.00																			
USAsian	-0.00	-0.06	0.05	-0.05	1.00																		
IntAsian	-0.05	-0.07	0.02	-0.19	-0.14	1.00																	
IntOther	0.01	0.18	-0.06	-0.17	-0.12	-0.42	1.00																
GREVerbalPct	0.03	-0.06	-0.04	0.00	0.04	-0.12	-0.15	1.00															
GREQuantPct	-0.02	-0.16	-0.10	-0.18	0.00	0.44	-0.10	0.16	1.00														
GREAnalyticPct	0.05	-0.06	0.03	0.08	0.08	-0.37	-0.08	0.60	-0.20	1.00													
UgradGPA	-0.02	-0.29	0.07	-0.13	-0.02	0.02	0.00	0.06	0.12	0.05	1.00												
TOEFL/IELTS	-0.01	-0.07	0.01	-0.02	0.01	0.04	0.00	0.24	0.12	0.19	0.00	1.00											
EliteUSUni	0.01	-0.12	0.02	0.12	0.14	-0.12	-0.22	0.16	-0.00	0.19	-0.01	-0.02	1.00										
EliteUSLA	-0.02	-0.02	0.04	0.04	0.04	-0.08	-0.09	0.12	-0.01	0.13	-0.02	-0.00	-0.11	1.00									
EliteForeign	-0.00	-0.04	-0.00	-0.06	-0.04	0.09	0.09	0.02	0.08	-0.02	0.01	0.04	-0.12	-0.06	1.00								
OtherForeign	-0.02	0.20	-0.04	-0.23	-0.14	0.34	0.39	-0.26	0.20	-0.39	0.02	0.02	-0.43	-0.21	-0.22	1.00							
GradDegree	0.00	0.41	-0.08	-0.13	-0.09	0.21	0.15	-0.14	0.05	-0.20	-0.22	0.03	-0.21	-0.10	0.05	0.37	1.00						
WorkExper	0.01	0.33	0.05	0.05	0.01	-0.18	0.11	0.01	-0.15	0.11	-0.08	-0.03	-0.02	0.03	-0.03	-0.01	0.10	1.00					
#ProfRecom	-0.02	-0.19	-0.04	-0.04	0.01	0.11	-0.09	0.01	0.09	-0.04	0.14	0.03	-0.02	0.02	-0.00	-0.02	-0.03	-0.18	1.00				
#ProlificRecom	0.01	-0.06	-0.02	-0.07	-0.01	0.24	-0.10	-0.01	0.25	-0.11	0.04	0.10	-0.01	-0.01	0.06	0.08	0.17	-0.09	0.19	1.00			
MissingGRE	0.09	0.15	0.05	0.11	-0.01	-0.22	0.17	0.09	-0.33	0.17	-0.09	-0.10	-0.03	-0.04	-0.03	-0.01	0.02	0.10	-0.08	-0.20	1.00		
MissingUgradGPA	-0.01	0.18	-0.04	-0.24	-0.15	0.36	0.42	-0.24	0.21	-0.38	0.02	0.04	-0.46	-0.23	0.23	0.83	0.37	-0.02	-0.03	0.10	-0.01	1.00	
MissingTOEFL/IELTS	0.05	-0.07	0.03	0.16	0.11	-0.32	-0.22	0.16	-0.24	0.32	-0.02	-0.02	0.29	0.14	-0.04	-0.58	-0.20	0.05	-0.07	-0.05	0.12	-0.58	1.00
Observations	6222																						

Reduced-Form Summary

A3: Logistic Regression Results (Matriculation)

Table 11a: Logistic Regression Results (Matriculation)

Matriculate	(1) Pre Coefs	(2) Pre AMEs	(3) Lasso	(4) Post Coefs	(5) Post AMEs
CovidYear	0.1384	0.0232			
	(0.4306)	(0.0724)			
WinsorAge	0.0261	0.0044			
	(0.0900)	(0.0152)			
Female	-0.6244*	-0.1049*	-0.3914	-0.6158*	-0.1037*
	(0.3570)	(0.0589)		(0.3471)	(0.0573)
International	0.7372	0.1239	0.1687	0.6690	0.1127
	(0.5175)	(0.0856)		(0.4693)	(0.0779)
GREVerbalPct	-0.0224*	-0.0038*	-0.0194	-0.0215*	-0.0036*
	(0.0130)	(0.0021)		(0.0123)	(0.0020)
GREQuantPct	-0.0609*	-0.0102*	-0.0425	-0.0631*	-0.0106*
	(0.0348)	(0.0058)		(0.0341)	(0.0056)
GREAnalyticPct	0.0034	0.0006			
	(0.0091)	(0.0015)			
UgradGPA	-4.1670***	-0.7001***	-2.2674	-4.1144***	-0.6932***
	(1.6083)	(0.2570)		(1.4501)	(0.2319)
TOEFL/IELTS	-0.3597	-0.0604	-0.1628	-0.2931	-0.0494
	(0.5858)	(0.0984)		(0.5263)	(0.0887)
EliteUgrad	-0.9465*	-0.1590*	-0.3943	-0.9245*	-0.1558*
	(0.4954)	(0.0827)		(0.4844)	(0.0816)
GradDegree	-0.2158	-0.0363			
	(0.4760)	(0.0799)			
WorkExper	-0.8483**	-0.1425**	-0.6164	-0.7994**	-0.1347**
	(0.4006)	(0.0666)		(0.3458)	(0.0572)
#ProfRecom	0.0296	0.0050			
	(0.2316)	(0.0389)			
#ProlificRecom	0.0268	0.0045			
	(0.1948)	(0.0328)			
AdvMath	-1.0856***	-0.1824***	-0.8427	-1.0371***	-0.1747***
	(0.3627)	(0.0574)		(0.3463)	(0.0548)
MissingUgradGPA	-2.1263***	-0.3573***	-0.9377	-2.0496***	-0.3453***
	(0.8113)	(0.1304)		(0.7114)	(0.1135)
MissingTOEFL/IELTS	-0.1722	-0.0289			
	(0.6110)	(0.1026)			
Observations	231	231	231	231	231
Pseudo-R^2	0.1469		0.1288	0.1445	
CV Pseudo-R^2	-0.0928		0.0112	0.0485	

Robust standard errors in parentheses: *p<0.10, **p<0.05, ***p<0.01.

- **Positive ($p < .05$):** None
- **Negative ($p < .05$):** UgradGPA, WorkExper, AdvMath, MissingUgradGPA

Post-Lasso Logistic Regression AMEs

A3: Different Determinants: Reject

Table 12a: Wald Test Results (Different)

	DV = Accept		DV = Success	
	Economics	Non-Economics	Economics	Non-Economics
GREQuantPct	0.0145***	0.0017***	0.0193***	0.0006
	(0.0012)	(0.0006)	(0.0014)	(0.0012)
Gender	0.0454***	0.0255***	-0.0251	0.0070
	(0.0140)	(0.0079)	(0.0200)	(0.0161)
Demographic1	-0.0604***	-0.0109	-0.0647**	-0.0214
	(0.0200)	(0.0103)	(0.0267)	(0.0205)
Demographic2	0.0150	0.0003	0.0313	-0.0105
	(0.0200)	(0.0091)	(0.0284)	(0.0192)
AdvMath	0.0279*		0.0600***	
	(0.0156)		(0.0202)	
ComScore	0.0217***	0.0164***	0.0187***	0.0336***
	(0.0039)	(0.0025)	(0.0052)	(0.0041)
NonEconomics1		-0.0019		0.2120***
		(0.0086)		(0.0219)
Obs | Pseudo-R^2	5000	0.1488	5000	0.0758
Wald Stat | P-Val	112.5897	0.0000	124.7379	0.0000

Robust standard errors in parentheses: *p<0.10, **p<0.05, ***p<0.01.

Acceptance vs. Success AMEs

A3: Same Determinants: Don't Reject

Table 12b: Wald Test Results (Same)

	DV = Accept		DV = Success	
	Economics	Non-Economics	Economics	Non-Economics
GREQuantPct	0.0146***	0.0155***	0.0193***	0.0208***
	(0.0012)	(0.0007)	(0.0014)	(0.0011)
Gender	0.0455***	0.0377***	-0.0253	-0.0090
	(0.0140)	(0.0081)	(0.0200)	(0.0161)
Demographic1	-0.0607***	-0.0886***	-0.0637**	-0.0556***
	(0.0200)	(0.0115)	(0.0267)	(0.0202)
Demographic2	0.0148	0.0177*	0.0321	0.0051
	(0.0200)	(0.0091)	(0.0284)	(0.0193)
AdvMath	0.0279*		0.0597***	
	(0.0156)		(0.0202)	
ComScore	0.0216***	0.0191***	0.0187***	0.0137***
	(0.0039)	(0.0023)	(0.0052)	(0.0041)
NonEconomics1		0.0401***		0.3515***
		(0.0107)		(0.0205)
Obs | Pseudo-R^2	5000	0.3251	5000	0.1431
Wald Stat | P-Val	3.1018	0.6843	3.0042	0.6993

Robust standard errors in parentheses: *p<0.10, **p<0.05, ***p<0.01.

Acceptance vs. Success AMEs

A3: Full Wald Test Results (Different)

Table 13a: Wald Test Results (Different)

	DV = Accept				DV = Success			
	Economics		Non-Economics		Economics		Non-Economics	
	Coef	AME	Coef	AME	Coef	AME	Coef	AME
Intercept	-16.3291***	-1.5784***	-8.4753***	-0.3642***	-10.4581***	-1.9104***	-3.2236***	-0.5997***
	(1.1274)	(0.0955)	(0.8673)	(0.0412)	(0.7237)	(0.1070)	(0.4018)	(0.0728)
GREQuantPct	0.1502***	0.0145***	0.0402***	0.0017***	0.1058***	0.0193***	0.0034	0.0006
	(0.0131)	(0.0012)	(0.0128)	(0.0006)	(0.0088)	(0.0014)	(0.0062)	(0.0012)
Gender	0.4702***	0.0454***	0.5942***	0.0255***	-0.1372	-0.0251	0.0375	0.0070
	(0.1473)	(0.0140)	(0.1820)	(0.0079)	(0.1095)	(0.0200)	(0.0868)	(0.0161)
Demographic1	-0.6246***	-0.0604***	-0.2541	-0.0109	-0.3544**	-0.0647**	-0.1152	-0.0214
	(0.2085)	(0.0200)	(0.2393)	(0.0103)	(0.1467)	(0.0267)	(0.1103)	(0.0205)
Demographic2	0.1555	0.0150	0.0081	0.0003	0.1713	0.0313	-0.0562	-0.0105
	(0.2070)	(0.0200)	(0.2109)	(0.0091)	(0.1557)	(0.0284)	(0.1030)	(0.0192)
AdvMath	0.2886*	0.0279*			0.3284***	0.0600***		
	(0.1611)	(0.0156)			(0.1112)	(0.0202)		
ComScore	0.2241***	0.0217***	0.3817***	0.0164***	0.1026***	0.0187***	0.1808***	0.0336***
	(0.0413)	(0.0039)	(0.0528)	(0.0025)	(0.0287)	(0.0052)	(0.0228)	(0.0041)
NonEconomics1			-0.0452	-0.0019			1.1393***	0.2120***
			(0.1995)	(0.0086)			(0.1219)	(0.0219)
Obs | Pseudo-R^2	5000	0.1488			5000	0.0758		
LL | Param | AIC	-1155.7	14	2339.5		-2747.2	14	5522.4	
Wald Stat | DF | P-Val	112.5897	5	0.0000		124.7379	5	0.0000	

Robust standard errors in parentheses: *p<0.10, **p<0.05, ***p<0.01.

Acceptance vs. Success AMEs

A3: Full Wald Test Results (Same)

Table 13b: Wald Test Results (Same)

	DV = Accept				DV = Success			
	Economics		Non-Economics		Economics		Non-Economics	
	Coef	AME	Coef	AME	Coef	AME	Coef	AME
Intercept	-16.3848***	-1.5822***	-28.5524***	-1.3677***	-10.4586***	-1.9105***	-10.2610***	-1.8514***
	(1.1315)	(0.0956)	(1.4963)	(0.0500)	(0.7236)	(0.1070)	(0.4815)	(0.0628)
GREQuantPct	0.1509***	0.0146***	0.3245***	0.0155***	0.1058***	0.0193***	0.1154***	0.0208***
	(0.0131)	(0.0012)	(0.0179)	(0.0007)	(0.0088)	(0.0014)	(0.0070)	(0.0011)
Gender	0.4714***	0.0455***	0.7880***	0.0377***	-0.1384	-0.0253	-0.0497	-0.0090
	(0.1475)	(0.0140)	(0.1696)	(0.0081)	(0.1095)	(0.0200)	(0.0895)	(0.0161)
Demographic1	-0.6287***	-0.0607***	-1.8488***	-0.0886***	-0.3486**	-0.0637**	-0.3079***	-0.0556***
	(0.2088)	(0.0200)	(0.2445)	(0.0115)	(0.1467)	(0.0267)	(0.1123)	(0.0202)
Demographic2	0.1531	0.0148	0.3703*	0.0177*	0.1756	0.0321	0.0282	0.0051
	(0.2072)	(0.0200)	(0.1929)	(0.0091)	(0.1558)	(0.0284)	(0.1069)	(0.0193)
AdvMath	0.2889*	0.0279*			0.3267***	0.0597***		
	(0.1612)	(0.0156)			(0.1112)	(0.0202)		
ComScore	0.2241***	0.0216***	0.3994***	0.0191***	0.1026***	0.0187***	0.0757***	0.0137***
	(0.0413)	(0.0039)	(0.0506)	(0.0023)	(0.0287)	(0.0052)	(0.0228)	(0.0041)
NonEconomics1			0.8376***	0.0401***			1.9483***	0.3515***
			(0.2297)	(0.0107)			(0.1236)	(0.0205)
Obs | Pseudo-R^2	5000	0.3251			5000	0.1431		
LL | Param | AIC	-1130.4	14	2288.8		-2691.4	14	5410.8	
Wald Stat | DF | P-Val	3.1018	5	0.6843		3.0042	5	0.6993	

Robust standard errors in parentheses: *p<0.10, **p<0.05, ***p<0.01.

Acceptance vs. Success AMEs

A3: Wald Test Summary Statistics (Different)

Table 14a: Wald Test Summary Statistics (Different)

	Economics		Non-Economics 1		Non-Economics 2	
	Mean	SD	Mean	SD	Mean	SD
Accept	0.1335	0.3401	0.0452	0.2078	0.0543	0.2266
Success	0.3000	0.4583	0.3126	0.4636	0.1314	0.3379
GREQuantPct	84.8390	7.5405	65.1343	7.4495	65.6114	7.6706
Gender	0.3935	0.4885	0.3952	0.4889	0.5914	0.4916
Demographic1	0.5005	0.5000	0.3091	0.4621	0.2600	0.4386
Demographic2	0.2505	0.4333	0.2957	0.4563	0.3414	0.4742
AdvMath	0.5095	0.4999				
ComScore	4.9325	1.9877	6.0191	2.0205	6.0243	2.0038
Observations	2000		2300		700	

Acceptance vs. Success AMEs

A3: Wald Test Summary Statistics (Same)

Table 14b: Wald Test Summary Statistics (Same)

	Economics		Non-Economics 1		Non-Economics 2	
	Mean	SD	Mean	SD	Mean	SD
Accept	0.1335	0.3401	0.0900	0.2862	0.0786	0.2691
Success	0.3000	0.4583	0.4057	0.4910	0.1157	0.3199
GREQuantPct	84.8390	7.5405	65.1343	7.4495	65.6114	7.6706
Gender	0.3935	0.4885	0.3952	0.4889	0.5914	0.4916
Demographic1	0.5005	0.5000	0.3091	0.4621	0.2600	0.4386
Demographic2	0.2505	0.4333	0.2957	0.4563	0.3414	0.4742
AdvMath	0.5095	0.4999				
ComScore	4.9325	1.9877	6.0191	2.0205	6.0243	2.0038
Observations	2000		2300		700	

Acceptance vs. Success AMEs

A3: Wald Test Correlation Matrix (Different)

Table 15a: Wald Test Correlation Matrix (Different)

	Acc	Suc	GRE	Gen	Dem1	Dem2	Com	NEcon1	NEcon2
Accept	1								
Success	0.0885	1							
GREQuantPct	0.2376	0.1167	1						
Gender	0.0582	-0.0220	-0.0795	1					
Demographic1	0.0152	-0.0004	0.3377	-0.0136	1				
Demographic2	0.0078	0.0003	-0.0876	-0.0209	-0.4918	1			
ComScore	0.1437	0.1500	-0.0770	0.0980	-0.1567	-0.0359	1		
NonEconomics1	-0.1232	0.0624	-0.6017	-0.0501	-0.1326	0.0238	0.1930	1	
NonEconomics2	-0.0405	-0.1352	-0.2472	0.1384	-0.0988	0.0514	0.0854	-0.3724	1
Observations	5000								

Acceptance vs. Success AMEs

A3: Wald Test Correlation Matrix (Same)

Table 15b: Wald Test Correlation Matrix (Same)

	Acc	Suc	GRE	Gen	Dem1	Dem2	Com	NEcon1	NEcon2
Accept	1								
Success	0.1603	1							
GREQuantPct	0.2772	0.1665	1						
Gender	0.0484	-0.0581	-0.0795	1					
Demographic1	-0.0233	0.0199	0.3377	-0.0136	1				
Demographic2	0.0487	0.0148	-0.0876	-0.0209	-0.4918	1			
ComScore	0.2045	0.1486	-0.0770	0.0980	-0.1567	-0.0359	1		
NonEconomics1	-0.0474	0.1636	-0.6017	-0.0501	-0.1326	0.0238	0.1930	1	
NonEconomics2	-0.0357	-0.1787	-0.2472	0.1384	-0.0988	0.0514	0.0854	-0.3724	1
Observations	5000								

Acceptance vs. Success AMEs

A4: Simulated Summary Statistics (Suboptimal)

Table 16a: Simulated Summary Statistics (Suboptimal)

	Mean	SD
Transition	0.3910	0.4880
Accept	0.1350	0.3417
Success	0.3040	0.4600
GREQuantPct	84.9310	7.5286
Gender	0.3970	0.4893
Demographic1	0.5410	0.4983
Demographic2	0.2600	0.4386
AdvMath	0.5300	0.4991
ComScore	5.1470	2.0277
YearTransMore	0.5000	0.5000
Observations	1000	

Year-Dynamic Unrestricted Estimates (Suboptimal)

A4: Simulated Summary Statistics (Optimal)

Table 16b: Simulated Summary Statistics (Optimal)

	Mean	SD
Transition	0.3940	0.4886
Accept	0.1400	0.3470
Success	0.3040	0.4600
GREQuantPct	84.9310	7.5286
Gender	0.3970	0.4893
Demographic1	0.5410	0.4983
Demographic2	0.2600	0.4386
AdvMath	0.5300	0.4991
ComScore	5.1470	2.0277
YearTransMore	0.5000	0.5000
Observations	1000	

Year-Dynamic Unrestricted Estimates (Optimal)

A4: Simulated Correlation Matrix (Suboptimal)

Table 17a: Simulated Correlation Matrix (Suboptimal)

	Trans	Acc	Suc	GRE	Fem	Asn	Oth	Math	Com	Year
Transition	1									
Accept	0.4930	1								
Success	0.1164	0.0379	1							
GREQuantPct	0.2550	0.2081	0.3225	1						
Gender	0.0200	0.0503	-0.0164	-0.0398	1					
Demographic1	-0.0351	-0.0472	0.0023	0.2688	-0.0032	1				
Demographic2	0.0670	0.0394	0.0642	-0.0579	-0.0476	-0.6435	1			
AdvMath	0.0894	0.1140	0.1868	0.2799	-0.0181	0.1941	-0.0996	1		
ComScore	0.0915	0.1662	0.1204	0.2029	0.0783	-0.0827	-0.0396	0.2372	1	
YearTransMore	0.1865	-0.0497	0.0217	-0.0410	-0.0225	-0.0341	0.0593	0.0521	0.0192	1
Observations	1000									

Year-Dynamic Unrestricted Estimates (Suboptimal)

A4: Simulated Correlation Matrix (Optimal)

Table 17b: Simulated Correlation Matrix (Optimal)

	Trans	Acc	Suc	GRE	Fem	Asn	Oth	Math	Com	Year
Transition	1									
Accept	0.5004	1								
Success	0.1300	0.0905	1							
GREQuantPct	0.2876	0.3038	0.3225	1						
Gender	-0.0185	0.0084	-0.0164	-0.0398	1					
Demographic1	-0.0006	0.0189	0.0023	0.2688	-0.0032	1				
Demographic2	0.0493	0.0105	0.0642	-0.0579	-0.0476	-0.6435	1			
AdvMath	0.0991	0.1605	0.1868	0.2799	-0.0181	0.1941	-0.0996	1		
ComScore	0.0980	0.1271	0.1204	0.2029	0.0783	-0.0827	-0.0396	0.2372	1	
YearTransMore	0.1678	-0.0692	0.0217	-0.0410	-0.0225	-0.0341	0.0593	0.0521	0.0192	1
Observations	1000									

Year-Dynamic Unrestricted Estimates (Optimal)

A4: Full Year-Dynamic Unrestricted Estimates (Suboptimal)

Table 18a: Year-Dynamic Unrestricted Estimates (Suboptimal)

	FAdvMath		FComScore	Transition		Accept		Success	
	Coef	AME	Coef	Coef	AME	Coef	AME	Coef	AME
Intercept	-6.1586***	-1.3913***	0.5480	-8.6113***	-1.8072***	-4.6409***	-0.8906***	-8.4142***	-1.7374***
	(0.8297)	(0.1654)	(0.7283)	(0.9390)	(0.1610)	(1.6387)	(0.2989)	(1.7756)	(0.3129)
GREQuantPct	0.0710***	0.0160***	0.0581***	0.0923***	0.0194***	0.0386**	0.0074**	0.0846***	0.0175***
	(0.0099)	(0.0020)	(0.0088)	(0.0110)	(0.0020)	(0.0191)	(0.0036)	(0.0211)	(0.0039)
Gender	-0.0381	-0.0086	0.3310***	0.1796	0.0377	0.3556	0.0682	-0.0468	-0.0097
	(0.1363)	(0.0308)	(0.1204)	(0.1418)	(0.0297)	(0.2307)	(0.0441)	(0.2303)	(0.0475)
Demographic1	0.5198***	0.1174***	-1.2830***	-0.4878**	-0.1024**	-0.5489	-0.1053*	-0.2506	-0.0517
	(0.1800)	(0.0400)	(0.1529)	(0.1990)	(0.0412)	(0.3363)	(0.0638)	(0.3422)	(0.0700)
Demographic2	-0.0415	-0.0094	-0.9475***	0.0313	0.0066	-0.0869	-0.0167	0.5529*	0.1142*
	(0.2000)	(0.0452)	(0.1759)	(0.2102)	(0.0441)	(0.3517)	(0.0675)	(0.3207)	(0.0659)
AdvMath			0.8895***			0.4169	0.0800*	0.6588***	0.1360***
			(0.1239)			(0.2549)	(0.0482)	(0.2507)	(0.0504)
ComScore						0.2201***	0.0422***	0.0048	0.0010
						(0.0666)	(0.0120)	(0.0584)	(0.0121)
YearTransMore				0.8992***	0.1887***	-1.1992***	-0.2301***		
				(0.1418)	(0.0273)	(0.2380)	(0.0398)		
$\sqrt{\text{MeanSqError}}$			1.8844***						
			(0.0398)						
Obs | Pseudo-R^2	1000	0.0596							
LL | Param | AIC	-3758.1	33	7582.1						

Robust standard errors in parentheses: *p<0.10, **p<0.05, ***p<0.01.

Year-Dynamic Unrestricted Estimates (Suboptimal)

A4: Full Year-Dynamic Unrestricted Estimates (Optimal)

Table 18b: Year-Dynamic Unrestricted Estimates (Optimal)

	FAdvMath		FComScore	Transition		Accept		Success	
	Coef	AME	Coef	Coef	AME	Coef	AME	Coef	AME
Intercept	-6.1391***	-1.3875***	0.5474	-9.2064***	-1.9245***	-8.8857***	-1.6359***	-8.7036***	-1.8098***
	(0.8288)	(0.1654)	(0.7284)	(0.9500)	(0.1576)	(1.7825)	(0.2813)	(1.8073)	(0.3173)
GREQuantPct	0.0708***	0.0160***	0.0581***	0.0998***	0.0209***	0.0937***	0.0173***	0.0879***	0.0183***
	(0.0099)	(0.0020)	(0.0088)	(0.0112)	(0.0019)	(0.0204)	(0.0033)	(0.0213)	(0.0039)
Gender	-0.0384	-0.0087	0.3312***	0.0009	0.0002	0.1963	0.0361	-0.0426	-0.0089
	(0.1363)	(0.0308)	(0.1204)	(0.1424)	(0.0298)	(0.2429)	(0.0448)	(0.2313)	(0.0481)
Demographic1	0.5189***	0.1173***	-1.2807***	-0.3536*	-0.0739*	-0.4632	-0.0853	-0.3130	-0.0651
	(0.1800)	(0.0400)	(0.1529)	(0.2007)	(0.0416)	(0.3599)	(0.0659)	(0.3443)	(0.0707)
Demographic2	-0.0429	-0.0097	-0.9447***	0.0434	0.0091	-0.1716	-0.0316	0.5339	0.1110
	(0.1999)	(0.0452)	(0.1759)	(0.2140)	(0.0447)	(0.3749)	(0.0691)	(0.3263)	(0.0676)
AdvMath			0.8894***			0.7280***	0.1340***	0.5854**	0.1217**
			(0.1239)			(0.2611)	(0.0463)	(0.2519)	(0.0512)
ComScore						0.0908	0.0167	0.0227	0.0047
						(0.0623)	(0.0113)	(0.0574)	(0.0119)
YearTransMore				0.8263***	0.1727***	-1.2645***	-0.2328***		
				(0.1421)	(0.0276)	(0.2443)	(0.0379)		
$\sqrt{\text{MeanSqError}}$			1.8844***						
			(0.0398)						
Obs | Pseudo-R^2	1000	0.0628							
LL | Param | AIC	-3753.7	33	7573.4						

Robust standard errors in parentheses: *p<0.10, **p<0.05, ***p<0.01.

Year-Dynamic Unrestricted Estimates (Optimal)

A4: Full Year-Static Restricted Estimates (Suboptimal)

Table 19a: Year-Static Restricted Estimates (Suboptimal)

	Cutoff1	$P(\text{Cutoff})_1$	Cutoff2	$P(\text{Cutoff})_2$	Success1	Success2	Sigma
Intercept	0.1539	53.84%	-0.5306**	37.04%	-10.3327***	-7.2584***	
	(0.2749)	(40.49%, 66.66%)	(0.2154)	(27.83%, 47.29%)	(1.9333)	(2.2514)	
GREQuantPct					0.1123***	0.0663**	
					(0.0227)	(0.0260)	
Gender					0.1010	0.0839	
					(0.1144)	(0.1650)	
Demographic1					-0.4233**	-0.3725	
					(0.1783)	(0.2547)	
Demographic2					0.1588	0.2935	
					(0.1773)	(0.2525)	
AdvMath						0.5525***	
						(0.1957)	
ComScore						0.1161***	
						(0.0447)	
YearTransMore	-0.9253***	31.62%	1.2103***	66.37%			
	(0.2622)	(26.62%, 37.07%)	(0.4178)	(47.08%, 81.40%)			
Sigma							0.2473***
							(0.0680)
Observations	1000						
LL | Param | AIC	-1625.8	17	3285.6				
LR Stat | DF | P-Val	19.2965	9	0.0228				

Robust standard errors in parentheses: *p<0.10, **p<0.05, ***p<0.01. Confidence intervals are 95%.

▸▸ Year-Static Restricted Estimates (Suboptimal)

A4: Full Year-Static Restricted Estimates (Optimal)

Table 19b: Year-Static Restricted Estimates (Optimal)

	Cutoff1	$P(\text{Cutoff})_1$	Cutoff2	$P(\text{Cutoff})_2$	Success1	Success2	Sigma
Intercept	-0.0094	49.77%	-0.5492***	36.60%	-10.0587***	-8.9338***	
	(0.2357)	(38.43%, 61.13%)	(0.1882)	(28.53%, 45.50%)	(2.2082)	(2.4363)	
GREQuantPct					0.1090***	0.0882***	
					(0.0259)	(0.0275)	
Gender					0.0070	0.0220	
					(0.1080)	(0.1620)	
Demographic1					-0.3346*	-0.2945	
					(0.1803)	(0.2626)	
Demographic2					0.1444	0.2881	
					(0.1702)	(0.2608)	
AdvMath						0.6055***	
						(0.1854)	
ComScore						0.0657	
						(0.0419)	
YearTransMore	-0.7509***	31.86%	1.1488***	64.56%			
	(0.2200)	(27.27%, 36.83%)	(0.3847)	(47.28%, 78.72%)			
Sigma							0.2149***
							(0.0597)
Observations	1000						
LL | Param | AIC	-1615.9	17	3265.9				
LR Stat | DF | P-Val	8.4729	9	0.4873				

Robust standard errors in parentheses: *p<0.10, **p<0.05, ***p<0.01. Confidence intervals are 95%.

Year-Static Restricted Estimates (Optimal)

A4: Year-Static Unrestricted Estimates (Suboptimal)

Table 20a: Year-Static Unrestricted Estimates (Suboptimal)

	Transition		Accept		Success1		Success2	
	Coef	AME	Coef	AME	Coef	AME	Coef	AME
Intercept	-8.5777***	-1.8014***	-4.7849***	-0.9157***	-10.5425***	-1.9666***	-8.3580***	-1.7285***
	(0.9369)	(0.1610)	(1.6496)	(0.2990)	(1.0566)	(0.1529)	(1.7683)	(0.3127)
GREQuantPct	0.0919***	0.0193***	0.0401**	0.0077**	0.1140***	0.0213***	0.0839***	0.0173***
	(0.0110)	(0.0020)	(0.0193)	(0.0036)	(0.0125)	(0.0019)	(0.0210)	(0.0039)
Gender	0.1789	0.0376	0.3374	0.0646	0.0044	0.0008	-0.0594	-0.0123
	(0.1417)	(0.0297)	(0.2315)	(0.0442)	(0.1509)	(0.0281)	(0.2300)	(0.0476)
Demographic1	-0.4843**	-0.1017**	-0.5416	-0.1036	-0.2944	-0.0549	-0.2355	-0.0487
	(0.1988)	(0.0412)	(0.3380)	(0.0639)	(0.2115)	(0.0392)	(0.3420)	(0.0701)
Demographic2	0.0338	0.0071	-0.0696	-0.0133	0.2505	0.0467	0.5612*	0.1161*
	(0.2101)	(0.0441)	(0.3531)	(0.0676)	(0.2214)	(0.0413)	(0.3209)	(0.0661)
AdvMath			0.4165	0.0797*			0.6465***	0.1337***
			(0.2555)	(0.0482)			(0.2502)	(0.0504)
ComScore			0.2219***	0.0425***			0.0059	0.0012
			(0.0668)	(0.0120)			(0.0583)	(0.0121)
YearTransMore	0.8980***	0.1886***	-1.2106***	-0.2317***				
	(0.1416)	(0.0273)	(0.2388)	(0.0397)				
Obs | Pseudo-R^2	1000	0.0988						
LL | Param | AIC	-1616.1	26	3284.3					

Robust standard errors in parentheses: *p<0.10, **p<0.05, ***p<0.01.

Year-Dynamic Unrestricted Estimates (Suboptimal)

A4: Year-Static Unrestricted Estimates (Optimal)

Table 20b: Year-Static Unrestricted Estimates (Optimal)

	Transition		Accept		Success1		Success2	
	Coef	AME	Coef	AME	Coef	AME	Coef	AME
Intercept	-9.1577***	-1.9164***	-9.2245***	-1.6855***	-10.5425***	-1.9666***	-8.4374***	-1.7657***
	(0.9469)	(0.1576)	(1.8167)	(0.2808)	(1.0566)	(0.1529)	(1.7772)	(0.3171)
GREQuantPct	0.0992***	0.0208***	0.0971***	0.0177***	0.1140***	0.0213***	0.0847***	0.0177***
	(0.0111)	(0.0019)	(0.0207)	(0.0033)	(0.0125)	(0.0019)	(0.0210)	(0.0039)
Gender	0.0002	0.0000	0.1897	0.0347	0.0044	0.0008	-0.0412	-0.0086
	(0.1422)	(0.0298)	(0.2448)	(0.0448)	(0.1509)	(0.0281)	(0.2299)	(0.0481)
Demographic1	-0.3518*	-0.0736*	-0.4248	-0.0776	-0.2944	-0.0549	-0.2785	-0.0583
	(0.2004)	(0.0416)	(0.3637)	(0.0662)	(0.2115)	(0.0392)	(0.3423)	(0.0709)
Demographic2	0.0435	0.0091	-0.1174	-0.0215	0.2505	0.0467	0.5504*	0.1152*
	(0.2137)	(0.0447)	(0.3788)	(0.0693)	(0.2214)	(0.0413)	(0.3256)	(0.0678)
AdvMath			0.7137***	0.1304***			0.5665**	0.1185**
			(0.2626)	(0.0463)			(0.2501)	(0.0513)
ComScore			0.0952	0.0174			0.0237	0.0050
			(0.0628)	(0.0113)			(0.0572)	(0.0119)
YearTransMore	0.8248***	0.1726***	-1.2833***	-0.2345***				
	(0.1419)	(0.0276)	(0.2467)	(0.0378)				
Obs | Pseudo-R^2	1000	0.1058						
LL | Param | AIC	-1611.7	26	3275.4					

Robust standard errors in parentheses: *p<0.10, **p<0.05, ***p<0.01.

▸▸ Year-Dynamic Unrestricted Estimates (Optimal)

A4: Year-Dynamic Restricted Estimates (Suboptimal)

Table 21a: Year-Dynamic Restricted Estimates (Suboptimal)

	FAdvMath	FComScore	Cutoff1	$L(\text{Cutoff})_1$	Cutoff2	$P(\text{Cutoff})_2$	Success	Sigma
Intercept	-6.1931***	0.5166	-0.4477	0.6391	-0.6118***	35.17%	-8.4870	
	(0.8371)	(0.7436)	(0.6919)	(0.1647, 2.4802)	(0.1802)	(27.59%, 43.57%)	(12.5846)	
GREQuantPct	0.0715***	0.0586***					0.0799	
	(0.0100)	(0.0090)					(0.1379)	
Gender	-0.0410	0.3267***					0.1457	
	(0.1361)	(0.1202)					(0.1426)	
Demographic1	0.5215***	-1.2825***					-0.3775	
	(0.1802)	(0.1530)					(0.5271)	
Demographic2	-0.0349	-0.9447***					0.2483	
	(0.1999)	(0.1760)					(0.5059)	
AdvMath		0.8948***					0.4141	
		(0.1239)					(0.4431)	
ComScore							0.1340**	
							(0.0628)	
YearTransMore			-0.0096	0.6330	0.8913	56.94%		
			(0.0626)	(0.1709, 2.3444)	(1.3618)	(9.04%, 94.62%)		
$\sqrt{\text{MeanSqError}}$		1.8840***						
		(0.0399)						
Sigma								0.1819
								(0.2909)
Observations	1000							
LL | Param | AIC	-3785.0	24	7618.0					
LR Stat | DF | P-Val	53.8131	9	0.0000					

Robust standard errors in parentheses: *p<0.10, **p<0.05, ***p<0.01. Confidence intervals are 95%.

Year-Static Restricted Estimates (Suboptimal)

A4: Year-Dynamic Restricted Estimates (Optimal)

Table 21b: Year-Dynamic Restricted Estimates (Optimal)

	FAdvMath	FComScore	Cutoff1	$L(\text{Cutoff})_1$	Cutoff2	$P(\text{Cutoff})_2$	Success	Sigma
Intercept	-6.1768***	0.5240	-0.5344***	0.5860	-0.5960***	35.52%	-8.7931***	
	(0.8229)	(0.7313)	(0.1440)	(0.4419, 0.7771)	(0.1541)	(28.94%, 42.70%)	(3.0648)	
GREQuantPct	0.0713***	0.0584***					0.0876***	
	(0.0099)	(0.0089)					(0.0334)	
Gender	-0.0391	0.3305***					0.0238	
	(0.1359)	(0.1204)					(0.1132)	
Demographic1	0.5230***	-1.2810***					-0.2855	
	(0.1803)	(0.1531)					(0.2036)	
Demographic2	-0.0371	-0.9441***					0.1727	
	(0.1999)	(0.1760)					(0.1999)	
AdvMath		0.8913***					0.5028**	
		(0.1239)					(0.1953)	
ComScore							0.0659*	
							(0.0384)	
YearTransMore			0.0245	0.6006	0.7803**	54.59%		
			(0.0515)	(0.4481, 0.8049)	(0.3189)	(40.35%, 68.12%)		
$\sqrt{\text{MeanSqError}}$		1.8849***						
		(0.0398)						
Sigma								0.1473***
								(0.0541)
Observations	1000							
LL | Param | AIC	-3773.5	24	7595.0					
LR Stat | DF | P-Val	39.6494	9	0.0000					

Robust standard errors in parentheses: *p<0.10, **p<0.05, ***p<0.01. Confidence intervals are 95%.

Year-Static Restricted Estimates (Optimal)

A4: Year-Dynamic Unrestricted Missing (Suboptimal)

Table 22a: Year-Dynamic Unrestricted Missing (Suboptimal)

	FStage1		FAdvMath		FComScore	Transition		Accept		Success	
	Coef	AME	Coef	AME	Coef	Coef	AME	Coef	AME	Coef	AME
Intercept	-5.1788***	-1.7932***	-2.9927*	-1.0548*	2.7507	-8.5772***	-1.8014***	-4.8978***	-0.9362***	-8.2901***	-1.7168***
	(0.5553)	(0.1624)	(1.7053)	(0.5911)	(2.3336)	(0.9369)	(0.1610)	(1.6572)	(0.2992)	(1.7618)	(0.3127)
GREQuantPct	0.0554***	0.0192***	0.0409**	0.0144**	0.0355	0.0918***	0.0193***	0.0415**	0.0079**	0.0832***	0.0172***
	(0.0066)	(0.0020)	(0.0167)	(0.0057)	(0.0226)	(0.0110)	(0.0020)	(0.0193)	(0.0036)	(0.0209)	(0.0039)
Gender	0.1094	0.0379	-0.1976	-0.0696	0.1937	0.1789	0.0376	0.3418	0.0653	-0.0589	-0.0122
	(0.0858)	(0.0296)	(0.1380)	(0.0482)	(0.1947)	(0.1417)	(0.0297)	(0.2318)	(0.0441)	(0.2296)	(0.0475)
Demographic1	-0.2859**	-0.0990**	0.2982	0.1051	-1.1999***	-0.4842**	-0.1017**	-0.5561	-0.1063*	-0.2415	-0.0500
	(0.1186)	(0.0406)	(0.1976)	(0.0691)	(0.2734)	(0.1988)	(0.0412)	(0.3383)	(0.0638)	(0.3411)	(0.0700)
Demographic2	0.0241	0.0083	-0.1464	-0.0516	-0.9202***	0.0339	0.0071	-0.0826	-0.0158	0.5526*	0.1144*
	(0.1266)	(0.0438)	(0.2000)	(0.0703)	(0.2915)	(0.2101)	(0.0441)	(0.3531)	(0.0675)	(0.3201)	(0.0660)
AdvMath					0.8786***			0.4132	0.0790	0.6481***	0.1342***
					(0.2057)			(0.2558)	(0.0482)	(0.2499)	(0.0504)
ComScore								0.2220***	0.0424***	0.0053	0.0011
								(0.0668)	(0.0120)	(0.0582)	(0.0121)
YearTransMore	0.5446***	0.1886***				0.8980***	0.1886***	-1.2072***	-0.2307***		
	(0.0850)	(0.0274)				(0.1416)	(0.0273)	(0.2391)	(0.0397)		
InvMills			-0.4189	-0.1476	-0.1894						
			(0.3872)	(0.1361)	(0.5612)						
$\sqrt{\text{MeanSqError}}$					1.8925***						
					(0.0662)						
Obs | Pseudo R-^{2}	1000	0.0760									
LL | Param | AIC	-2715.9	41	5513.9								

Robust standard errors in parentheses: *p<0.10, **p<0.05, ***p<0.01.

Year-Dynamic Unrestricted Estimates (Suboptimal)

A4: Year-Dynamic Unrestricted Missing (Optimal)

Table 22b: Year-Dynamic Unrestricted Missing (Optimal)

	FStage1		FAdvMath		FComScore	Transition		Accept		Success	
	Coef	AME	Coef	AME	Coef	Coef	AME	Coef	AME	Coef	AME
Intercept	-5.5333***	-1.9103***	-2.6740	-0.9412	2.9426	-9.1587***	-1.9166***	-9.4836***	-1.7254***	-8.2448***	-1.7310***
	(0.5668)	(0.1614)	(1.9361)	(0.6738)	(2.6765)	(0.9470)	(0.1576)	(1.8420)	(0.2807)	(1.7584)	(0.3170)
GREQuantPct	0.0599***	0.0207***	0.0373**	0.0131**	0.0342	0.0992***	0.0208***	0.0998***	0.0182***	0.0824***	0.0173***
	(0.0067)	(0.0020)	(0.0188)	(0.0065)	(0.0258)	(0.0111)	(0.0019)	(0.0210)	(0.0033)	(0.0208)	(0.0039)
Gender	0.0025	0.0009	-0.1822	-0.0641	0.1863	0.0002	0.0000	0.1969	0.0358	-0.0434	-0.0091
	(0.0860)	(0.0297)	(0.1380)	(0.0482)	(0.1918)	(0.1422)	(0.0298)	(0.2459)	(0.0448)	(0.2292)	(0.0481)
Demographic1	-0.2056*	-0.0710*	0.2973	0.1047	-1.2445***	-0.3519*	-0.0736*	-0.4210	-0.0766	-0.2654	-0.0557
	(0.1193)	(0.0409)	(0.1954)	(0.0683)	(0.2697)	(0.2004)	(0.0416)	(0.3655)	(0.0662)	(0.3411)	(0.0709)
Demographic2	0.0312	0.0108	-0.1242	-0.0437	-1.0245***	0.0433	0.0091	-0.1066	-0.0194	0.5579*	0.1171*
	(0.1280)	(0.0442)	(0.2051)	(0.0721)	(0.2997)	(0.2137)	(0.0447)	(0.3807)	(0.0693)	(0.3250)	(0.0679)
AdvMath					0.8964***			0.7077***	0.1288***	0.5718**	0.1200**
					(0.2088)			(0.2634)	(0.0463)	(0.2495)	(0.0513)
ComScore								0.0968	0.0176	0.0233	0.0049
								(0.0631)	(0.0113)	(0.0570)	(0.0120)
YearTransMore	0.4989***	0.1722***				0.8249***	0.1726***	-1.2813***	-0.2331***		
	(0.0852)	(0.0277)				(0.1419)	(0.0276)	(0.2479)	(0.0378)		
InvMills			-0.4587	-0.1615	-0.2035						
			(0.4255)	(0.1495)	(0.6179)						
$\sqrt{\text{MeanSqError}}$					1.9059***						
					(0.0667)						
Obs | Pseudo R^2	1000	0.0811									
LL | Param | AIC	-2720.3	41	5522.6								

Robust standard errors in parentheses: *p<0.10, **p<0.05, ***p<0.01.

Year-Dynamic Unrestricted Estimates (Optimal)

A4: Year-Dynamic Restricted Missing (Suboptimal)

Table 23a: Year-Dynamic Restricted Missing (Suboptimal)

	FStage1	FAdvMath	FComScore	Cutoff1	$L(\text{Cutoff})_1$	Cutoff2	$P(\text{Cutoff})_2$	Success	Sigma
Intercept	-5.1849***	-3.0077*	2.7390	-0.4529	0.6358	-0.6156***	35.08%	-8.3629	
	(0.5600)	(1.7125)	(2.3203)	(0.6380)	(0.1821, 2.2201)	(0.1808)	(27.49%, 43.51%)	(11.5276)	
GREQuantPct	0.0554***	0.0418**	0.0363					0.0786	
	(0.0066)	(0.0168)	(0.0226)					(0.1266)	
Gender	0.1106	-0.1963	0.1960					0.1511	
	(0.0858)	(0.1363)	(0.1938)					(0.1374)	
Demographic1	-0.2846**	0.2917	-1.2040***					-0.3901	
	(0.1188)	(0.1960)	(0.2717)					(0.5285)	
Demographic2	0.0225	-0.1595	-0.9260***					0.2394	
	(0.1268)	(0.1973)	(0.2899)					(0.4445)	
AdvMath			0.8890***					0.4501	
			(0.2057)					(0.4458)	
ComScore								0.1300**	
								(0.0579)	
YearTransMore	0.5474***			-0.0042	0.6331	0.8901	56.82%		
	(0.0861)			(0.0616)	(0.1890, 2.1209)	(1.2635)	(10.79%, 93.47%)		
InvMills		-0.4754	-0.2427						
		(0.3913)	(0.5594)						
$\sqrt{\text{MeanSqError}}$			1.8935***						
			(0.0666)						
Sigma									0.1805
									(0.2674)
Observations	1000								
LL | Param | AIC	-2742.5	32	5549.0						
LR Stat | DF | P-Val	53.1755	9	0.0000						

Robust standard errors in parentheses: *p<0.10, **p<0.05, ***p<0.01. Confidence intervals are 95%.

Year-Static Restricted Estimates (Suboptimal)

Table 23b: Year-Dynamic Restricted Missing (Optimal)

	FStage1	FAdvMath	FComScore	Cutoff1	$L(\text{Cutoff})_1$	Cutoff2	$P(\text{Cutoff})_2$	Success	Sigma
Intercept	-5.5371***	-2.6870	2.9441	-0.5459***	0.5793	-0.5863***	35.75%	-8.3634***	
	(0.5732)	(1.9557)	(2.6682)	(0.1161)	(0.4615, 0.7273)	(0.1500)	(29.31%, 42.74%)	(2.3193)	
GREQuantPct	0.0599***	0.0382**	0.0345					0.0826***	
	(0.0068)	(0.0190)	(0.0257)					(0.0250)	
Gender	0.0032	-0.1802	0.1850					0.0447	
	(0.0860)	(0.1357)	(0.1912)					(0.1096)	
Demographic1	-0.2061*	0.2902	-1.2455***					-0.2408	
	(0.1194)	(0.1936)	(0.2693)					(0.1838)	
Demographic2	0.0295	-0.1360	-1.0281***					0.1880	
	(0.1281)	(0.2022)	(0.2992)					(0.1935)	
AdvMath			0.9026***					0.4942***	
			(0.2088)					(0.1764)	
ComScore								0.0643*	
								(0.0372)	
YearTransMore	0.4995***			0.0281	0.5958	0.7546***	54.20%		
	(0.0857)			(0.0503)	(0.4697, 0.7558)	(0.2627)	(42.41%, 65.54%)		
InvMills		-0.5095	-0.2301						
		(0.4343)	(0.6188)						
$\sqrt{\text{MeanSqError}}$			1.9062***						
			(0.0667)						
Sigma									0.1418***
									(0.0414)
Observations	1000								
LL | Param | AIC	-2739.7	32	5543.4						
LR Stat | DF | P-Val	38.8065	9	0.0000						

Robust standard errors in parentheses: *p<0.10, **p<0.05, ***p<0.01. Confidence intervals are 95%.

Year-Static Restricted Estimates (Optimal)

A4: Year-Myopic Unrestricted Estimates (Suboptimal)

Table 24a: Year-Myopic Unrestricted Estimates (Suboptimal)

	FAdvMath		FComScore	Transition		Accept		Success	
	Coef	AME	Coef	Coef	AME	Coef	AME	Coef	AME
Intercept	0.1201*	0.5300***	4.6362***	-8.5778***	-1.8014***	-4.7827***	-0.9153***	-8.3592***	-1.7287***
	(0.0634)	(0.0158)	(0.0879)	(0.9369)	(0.1610)	(1.6494)	(0.2990)	(1.7684)	(0.3127)
GREQuantPct				0.0919***	0.0193***	0.0401**	0.0077**	0.0839***	0.0174***
				(0.0110)	(0.0020)	(0.0193)	(0.0036)	(0.0210)	(0.0039)
Gender				0.1788	0.0376	0.3374	0.0646	-0.0594	-0.0123
				(0.1417)	(0.0297)	(0.2315)	(0.0442)	(0.2300)	(0.0476)
Demographic1				-0.4846**	-0.1018**	-0.5415	-0.1036	-0.2355	-0.0487
				(0.1988)	(0.0412)	(0.3380)	(0.0639)	(0.3420)	(0.0701)
Demographic2				0.0335	0.0070	-0.0695	-0.0133	0.5612*	0.1161*
				(0.2101)	(0.0441)	(0.3531)	(0.0676)	(0.3209)	(0.0661)
AdvMath			0.9638***			0.4166	0.0797*	0.6464***	0.1337***
			(0.1243)			(0.2555)	(0.0482)	(0.2502)	(0.0504)
ComScore						0.2219***	0.0425***	0.0059	0.0012
						(0.0668)	(0.0120)	(0.0583)	(0.0121)
YearTransMore				0.8980***	0.1886***	-1.2106***	-0.2317***		
				(0.1416)	(0.0273)	(0.2388)	(0.0397)		
$\sqrt{\text{MeanSqError}}$			1.9698***						
			(0.0413)						
Obs | Pseudo-R^2	1000	0.0363							
LL | Param | AIC	-3851.0	25	7752.1						

Robust standard errors in parentheses: *p<0.10, **p<0.05, ***p<0.01.

Year-Dynamic Unrestricted Estimates (Suboptimal)

A4: Year-Myopic Unrestricted Estimates (Optimal)

Table 24b: Year-Myopic Unrestricted Estimates (Optimal)

	FAdvMath		FComScore	Transition		Accept		Success	
	Coef	AME	Coef	Coef	AME	Coef	AME	Coef	AME
Intercept	0.1201*	0.5300***	4.6362***	-9.1582***	-1.9165***	-9.2354***	-1.6874***	-8.4285***	-1.7639***
	(0.0634)	(0.0158)	(0.0879)	(0.9469)	(0.1576)	(1.8175)	(0.2808)	(1.7765)	(0.3171)
GREQuantPct				0.0992***	0.0208***	0.0972***	0.0178***	0.0846***	0.0177***
				(0.0111)	(0.0019)	(0.0207)	(0.0033)	(0.0210)	(0.0039)
Gender				0.0002	0.0000	0.1906	0.0348	-0.0419	-0.0088
				(0.1422)	(0.0298)	(0.2448)	(0.0448)	(0.2299)	(0.0481)
Demographic1				-0.3522*	-0.0737*	-0.4229	-0.0773	-0.2773	-0.0580
				(0.2004)	(0.0416)	(0.3637)	(0.0662)	(0.3423)	(0.0709)
Demographic2				0.0431	0.0090	-0.1152	-0.0211	0.5521*	0.1155*
				(0.2137)	(0.0447)	(0.3789)	(0.0693)	(0.3257)	(0.0678)
AdvMath			0.9638***			0.7138***	0.1304***	0.5680**	0.1189**
			(0.1243)			(0.2625)	(0.0463)	(0.2501)	(0.0513)
ComScore						0.0953	0.0174	0.0237	0.0050
						(0.0628)	(0.0113)	(0.0572)	(0.0119)
YearTransMore				0.8248***	0.1726***	-1.2820***	-0.2342***		
				(0.1419)	(0.0276)	(0.2467)	(0.0378)		
$\sqrt{\text{MeanSqError}}$			1.9698***						
			(0.0413)						
Obs | Pseudo-R^2	1000	0.0396							
LL | Param | AIC	-3846.6	25	7743.2						

Robust standard errors in parentheses: *p<0.10, **p<0.05, ***p<0.01.

Year-Dynamic Unrestricted Estimates (Optimal)

A4: Year-Myopic Restricted Estimates (Suboptimal)

Table 25a: Year-Myopic Restricted Estimates (Suboptimal)

	FAdvMath	FComScore	Cutoff1	$L(\text{Cutoff})_1$	Cutoff2	$P(\text{Cutoff})_2$	Success	Sigma
Intercept	0.1291**	4.6418***	-0.4609	0.6307	-0.6100***	35.21%	-8.4650	
	(0.0636)	(0.0884)	(0.6357)	(0.1814, 2.1926)	(0.1827)	(32.88%, 37.60%)	(10.9416)	
GREQuantPct							0.0819	
							(0.1199)	
Gender							0.1398	
							(0.1284)	
Demographic1							-0.4103	
							(0.4518)	
Demographic2							0.2056	
							(0.4868)	
AdvMath		0.9652***					0.3557	
		(0.1243)					(0.4351)	
ComScore							0.1123**	
							(0.0529)	
YearTransMore			-0.0046	0.6279	0.8797	56.70%		
			(0.0615)	(0.1876, 2.1019)	(1.2631)	(10.93%, 93.32%)		
$\sqrt{\text{MeanSqError}}$		1.9675***						
		(0.0412)						
Sigma								0.1803
								(0.2674)
Observations	1000							
LL | Param | AIC	-3881.2	16	7794.4					
LR Stat | DF | P-Val	60.3013	9	0.0000					

Robust standard errors in parentheses: *p<0.10, **p<0.05, ***p<0.01. Confidence intervals are 95%.

Year-Static Restricted Estimates (Suboptimal)

A4: Year-Myopic Restricted Estimates (Optimal)

Table 25b: Year-Myopic Restricted Estimates (Optimal)

	FAdvMath	FComScore	Cutoff1	$L(\text{Cutoff})_1$	Cutoff2	$P(\text{Cutoff})_2$	Success	Sigma
Intercept	0.1317**	4.6389***	-0.5593***	0.5716	-0.5909***	35.64%	-8.5595***	
	(0.0635)	(0.0879)	(0.1114)	(0.4595, 0.7111)	(0.1494)	(34.08%, 37.24%)	(2.1793)	
GREQuantPct							0.0869***	
							(0.0239)	
Gender							0.0343	
							(0.1085)	
Demographic1							-0.2998*	
							(0.1787)	
Demographic2							0.1207	
							(0.1762)	
AdvMath		0.9645***					0.4241**	
		(0.1244)					(0.1693)	
ComScore							0.0498	
							(0.0351)	
YearTransMore			0.0304	0.5892	0.7487***	53.94%		
			(0.0510)	(0.4695, 0.7394)	(0.2510)	(42.65%, 64.83%)		
$\sqrt{\text{MeanSqError}}$		1.9718***						
		(0.0414)						
Sigma								0.1403***
								(0.0391)
Observations	1000							
LL | Param | AIC	-3869.1	16	7770.3					
LR Stat | DF | P-Val	45.0826	9	0.0000					

Robust standard errors in parentheses: *p<0.10, **p<0.05, ***p<0.01. Confidence intervals are 95%.

Year-Static Restricted Estimates (Optimal)

A4: Year-Myopic Unrestricted Missing (Suboptimal)

Table 26a: Year-Myopic Unrestricted Missing (Suboptimal)

	FStage1		FAdvMath		FComScore	Transition		Accept		Success	
	Coef	AME	Coef	AME	Coef	Coef	AME	Coef	AME	Coef	AME
Intercept	-0.5244***	-0.1957***	0.3641	0.1419	4.8485***	-8.5775***	-1.8014***	-4.7843***	-0.9156***	-8.3574***	-1.7284***
	(0.0589)	(0.0192)	(0.3839)	(0.1490)	(0.5941)	(0.9369)	(0.1610)	(1.6495)	(0.2990)	(1.7682)	(0.3127)
GREQuantPct						0.0919***	0.0193***	0.0401**	0.0077**	0.0839***	0.0173***
						(0.0110)	(0.0020)	(0.0193)	(0.0036)	(0.0210)	(0.0039)
Gender						0.1788	0.0376	0.3374	0.0646	-0.0592	-0.0122
						(0.1417)	(0.0297)	(0.2315)	(0.0442)	(0.2300)	(0.0476)
Demographic1						-0.4842**	-0.1017**	-0.5415	-0.1036	-0.2351	-0.0486
						(0.1988)	(0.0412)	(0.3380)	(0.0639)	(0.3420)	(0.0701)
Demographic2						0.0339	0.0071	-0.0695	-0.0133	0.5614*	0.1161*
						(0.2101)	(0.0441)	(0.3531)	(0.0676)	(0.3210)	(0.0661)
AdvMath					0.9097***			0.4165	0.0797*	0.6464***	0.1337***
					(0.1967)			(0.2555)	(0.0482)	(0.2502)	(0.0504)
ComScore								0.2219***	0.0425***	0.0059	0.0012
								(0.0668)	(0.0120)	(0.0583)	(0.0121)
YearTransMore	0.4793***	0.1788***				0.8980***	0.1886***	-1.2106***	-0.2317***		
	(0.0814)	(0.0287)				(0.1416)	(0.0273)	(0.2388)	(0.0397)		
InvMills			-0.1547	-0.0603	-0.0030						
			(0.3964)	(0.1543)	(0.6083)						
$\sqrt{\text{MeanSqError}}$					1.9491***						
					(0.0676)						
Obs | Pseudo R^2	1000	0.0489									
LL | Param | AIC	-2795.4	29	5648.9								

Robust standard errors in parentheses: *p<0.10, **p<0.05, ***p<0.01.

Year-Dynamic Unrestricted Estimates (Suboptimal)

A4: Year-Myopic Unrestricted Missing (Optimal)

Table 26b: Year-Myopic Unrestricted Missing (Optimal)

	FStage1		FAdvMath		FComScore	Transition		Accept		Success	
	Coef	AME	Coef	AME	Coef	Coef	AME	Coef	AME	Coef	AME
Intercept	-0.4902***	-0.1843***	0.4285	0.1664	4.9569***	-9.1577***	-1.9164***	-9.2245***	-1.6855***	-8.4374***	-1.7657***
	(0.0586)	(0.0195)	(0.4250)	(0.1643)	(0.6578)	(0.9469)	(0.1576)	(1.8167)	(0.2808)	(1.7772)	(0.3171)
GREQuantPct						0.0992***	0.0208***	0.0971***	0.0177***	0.0847***	0.0177***
						(0.0111)	(0.0019)	(0.0207)	(0.0033)	(0.0210)	(0.0039)
Gender						0.0002	0.0000	0.1897	0.0347	-0.0412	-0.0086
						(0.1422)	(0.0298)	(0.2448)	(0.0448)	(0.2299)	(0.0481)
Demographic1						-0.3519*	-0.0736*	-0.4248	-0.0776	-0.2785	-0.0583
						(0.2004)	(0.0416)	(0.3637)	(0.0662)	(0.3423)	(0.0709)
Demographic2						0.0434	0.0091	-0.1174	-0.0214	0.5504*	0.1152*
						(0.2137)	(0.0447)	(0.3788)	(0.0693)	(0.3256)	(0.0678)
AdvMath					0.9270***			0.7136***	0.1304***	0.5665**	0.1185**
					(0.1981)			(0.2626)	(0.0463)	(0.2501)	(0.0513)
ComScore								0.0952	0.0174	0.0237	0.0050
								(0.0628)	(0.0113)	(0.0572)	(0.0119)
YearTransMore	0.4300***	0.1617***				0.8248***	0.1726***	-1.2833***	-0.2345***		
	(0.0811)	(0.0292)				(0.1419)	(0.0276)	(0.2467)	(0.0378)		
InvMills			-0.2068	-0.0803	-0.1171						
			(0.4399)	(0.1706)	(0.6787)						
$\sqrt{\text{MeanSqError}}$					1.9628***						
					(0.0678)						
Obs | Pseudo R-^{2}	1000	0.0522									
LL | Param | AIC	-2805.9	29	5669.8								

Robust standard errors in parentheses: *p<0.10, **p<0.05, ***p<0.01.

Year-Dynamic Unrestricted Estimates (Optimal)

A4: Year-Myopic Restricted Missing (Suboptimal)

Table 27a: Year-Myopic Restricted Missing (Suboptimal)

	FStage1	FAdvMath	FComScore	Cutoff1	$L(\text{Cutoff})_1$	Cutoff2	$P(\text{Cutoff})_2$	Success	Sigma
Intercept	-0.5219***	0.3660	4.8574***	-0.4584	0.6323	-0.6106***	35.19%	-8.4597	
	(0.0589)	(0.3889)	(0.6005)	(0.4992)	(0.2377, 1.6820)	(0.1783)	(27.68%, 43.51%)	(8.6873)	
GREQuantPct								0.0814	
								(0.0950)	
Gender								0.1396	
								(0.1268)	
Demographic1								-0.4047	
								(0.3758)	
Demographic2								0.2066	
								(0.3980)	
AdvMath			0.9145***					0.3654	
			(0.1964)					(0.3542)	
ComScore								0.1172**	
								(0.0505)	
YearTransMore	0.4753***			-0.0079	0.6274	0.8704	56.46%		
	(0.0813)			(0.0590)	(0.2422, 1.6247)	(0.9919)	(16.77%, 89.30%)		
InvMills		-0.1441	0.0077						
		(0.4020)	(0.6141)						
$\sqrt{\text{MeanSqError}}$			1.9501***						
			(0.0677)						
Sigma									0.1785
									(0.2089)
Observations	1000								
LL | Param | AIC	-2824.9	20	5689.7						
LR Stat | DF | P-Val	58.8213	9	0.0000						

Robust standard errors in parentheses: *p<0.10, **p<0.05, ***p<0.01. Confidence intervals are 95%.

⏩ Year-Static Restricted Estimates (Suboptimal)

A4: Year-Myopic Restricted Missing (Optimal)

Table 27b: Year-Myopic Restricted Missing (Optimal)

	FStage1	FAdvMath	FComScore	Cutoff1	$L(\text{Cutoff})_1$	Cutoff2	$P(\text{Cutoff})_2$	Success	Sigma
Intercept	-0.4903***	0.4347	4.9623***	-0.5519***	0.5758	-0.5852***	35.77%	-8.5581***	
	(0.0585)	(0.4277)	(0.6606)	(0.1068)	(0.4671, 0.7099)	(0.1489)	(29.38%, 42.72%)	(2.0776)	
GREQuantPct								0.0861***	
								(0.0226)	
Gender								0.0384	
								(0.1075)	
Demographic1								-0.2591	
								(0.1750)	
Demographic2								0.1470	
								(0.1796)	
AdvMath			0.9310***					0.4198**	
			(0.1981)					(0.1642)	
ComScore								0.0566	
								(0.0356)	
YearTransMore	0.4302***			0.0282	0.5923	0.7481***	54.06%		
	(0.0810)			(0.0501)	(0.4762, 0.7368)	(0.2432)	(43.09%, 64.65%)		
InvMills		-0.1978	-0.1119						
		(0.4424)	(0.6804)						
$\sqrt{\text{MeanSqError}}$			1.9632***						
			(0.0678)						
Sigma									0.1401***
									(0.0370)
Observations	1000								
LL | Param | AIC	-2827.7	20	5695.3						
LR Stat | DF | P-Val	43.5305	9	0.0000						

Robust standard errors in parentheses: *p<0.10, **p<0.05, ***p<0.01. Confidence intervals are 95%.

Year-Static Restricted Estimates (Optimal)

A4: Waitlist Summary Statistics (Suboptimal)

Table 28a: Waitlist Summary Statistics (Suboptimal)

	Mean	SD
Transition	0.3700	0.4828
Waitlist	0.3120	0.4633
Accept	0.1510	0.3580
Matriculate	0.0310	0.1733
Success	0.3100	0.4625
GREQuantPct	84.9310	7.5286
Gender	0.3970	0.4893
Demographic1	0.5500	0.4975
Demographic2	0.2620	0.4397
AdvMath	0.5300	0.4991
ComScore	5.1470	2.0277
MatScore	4.9370	2.2426
YearTransMat	0.5000	0.5000
Observations	1000	

Waitlist-Dynamic Unrestricted Estimates (Suboptimal)

A4: Waitlist Summary Statistics (Optimal)

Table 28b: Waitlist Summary Statistics (Optimal)

	Mean	SD
Transition	0.3650	0.4814
Waitlist	0.3240	0.4680
Accept	0.1500	0.3571
Matriculate	0.0390	0.1936
Success	0.3150	0.4645
GREQuantPct	84.9310	7.5286
Gender	0.3970	0.4893
Demographic1	0.5500	0.4975
Demographic2	0.2620	0.4397
AdvMath	0.5300	0.4991
ComScore	5.1470	2.0277
MatScore	4.9370	2.2426
YearTransMat	0.5000	0.5000
Observations	1000	

Waitlist-Dynamic Unrestricted Estimates (Optimal)

A4: Waitlist Correlation Matrix (Suboptimal)

Table 29a: Waitlist Correlation Matrix (Suboptimal)

	Trans	Wait	Acc	IM	Suc	GRE	Gen	Dem1	Dem2	Math	Com	Mat	Year
Transition	1												
Watilist	0.8787	1											
Accept	0.5503	0.2766	1										
Matriculate	0.2334	-0.0084	0.4241	1									
Success	0.0685	0.0760	-0.0049	-0.0700	1								
GREQuantPct	0.3041	0.2745	0.2057	0.0675	0.2520	1							
Gender	0.0428	0.0138	0.0288	-0.0390	-0.0533	-0.0398	1						
Demographic1	-0.0146	0.0017	-0.0340	0.0574	0.0413	0.2483	0.0068	1					
Demographic2	0.0804	0.0553	0.0472	-0.0016	-0.0208	-0.0918	-0.0605	-0.6587	1				
AdvMath	0.0660	0.0417	0.0502	0.0413	0.1243	0.2799	-0.0181	0.1953	-0.1042	1			
ComScore	0.0364	0.0268	0.0493	-0.1154	0.1146	0.2029	0.0783	-0.0960	-0.0869	0.2372	1		
MatScore	0.0622	0.0420	-0.0778	0.1774	-0.0496	-0.0945	-0.0383	0.0562	0.0370	-0.0479	-0.3571	1	
YearTransMat	0.1947	0.2029	-0.1480	0.0058	0.0000	-0.0410	-0.0225	-0.0241	0.0318	0.0521	0.0192	0.4383	1
Observations	1000												

Waitlist-Dynamic Unrestricted Estimates (Suboptimal)

A4: Waitlist Correlation Matrix (Optimal)

Table 29b: Waitlist Correlation Matrix (Optimal)

	Trans	Wait	Acc	IM	Suc	GRE	Gen	Dem1	Dem2	Math	Com	Mat	Year
Transition	1												
Watilist	0.9131	1											
Accept	0.5541	0.3614	1										
Matriculate	0.2657	0.0923	0.4796	1									
Success	0.0448	0.0135	0.0528	0.0302	1								
GREQuantPct	0.2503	0.1908	0.2389	0.0801	0.3210	1							
Gender	-0.0038	0.0191	-0.0489	-0.0262	-0.0310	-0.0398	1						
Demographic1	0.0136	0.0034	0.0478	0.0161	-0.0444	0.2483	0.0068	1					
Demographic2	0.0065	0.0005	-0.0146	0.0327	0.0513	-0.0918	-0.0605	-0.6587	1				
AdvMath	0.0647	0.0397	0.0645	0.0034	0.0994	0.2799	-0.0181	0.1953	-0.1042	1			
ComScore	0.0813	0.0710	0.0704	-0.1063	0.1557	0.2029	0.0783	-0.0960	-0.0869	0.2372	1		
MatScore	0.0167	-0.0215	-0.0869	0.2130	-0.0280	-0.0945	-0.0383	0.0562	0.0370	-0.0479	-0.3571	1	
YearTransMat	0.1641	0.1624	-0.1736	0.0052	-0.0624	-0.0410	-0.0225	-0.0241	0.0318	0.0521	0.0192	0.4383	1
Observations	1000												

Waitlist-Dynamic Unrestricted Estimates (Optimal)

A4: Full Waitlist-Dynamic Unrestricted Estimates (Suboptimal)

Table 30a: Waitlist-Dynamic Unrestricted Estimates (Suboptimal)

	FAdvMath		FComScore	F$\ddot{m}_2$	F$\overline{m_{2A}}$	Transition		Accept2		Accept3		Success	
	Coef	AME	Coef	Coef	Coef	Coef	AME	Coef	AME	Coef	AME	Coef	AME
Intercept	-6.2079***	-1.4002***	0.9526	5.4979***	0.1489***	-10.7210***	-2.1071***	1.0375	0.1332	3.6817	0.4845	-8.2484***	-1.7415***
	(0.8279)	(0.1646)	(0.7367)	(0.3634)	(0.0018)	(1.0460)	(0.1548)	(2.3164)	(0.2962)	(2.3327)	(0.3079)	(1.7721)	(0.3282)
GREQuantPct	0.0707***	0.0160***	0.0566***	-0.0082*		0.1109***	0.0218***	-0.0180	-0.0023	0.0471*	0.0062*	0.0844***	0.0178***
	(0.0099)	(0.0020)	(0.0088)	(0.0045)		(0.0119)	(0.0019)	(0.0253)	(0.0032)	(0.0271)	(0.0034)	(0.0210)	(0.0040)
Gender	-0.0397	-0.0090	0.3124***	-0.0468		0.3479**	0.0684**	0.3888	0.0499	-0.7248**	-0.0954**	-0.0186	-0.0039
	(0.1367)	(0.0308)	(0.1188)	(0.0637)		(0.1474)	(0.0286)	(0.2995)	(0.0386)	(0.3422)	(0.0442)	(0.2390)	(0.0505)
Demographic1	0.6068***	0.1369***	-1.5750***	0.0087		-0.1970	-0.0387	-0.1599	-0.0205	-1.1811**	-0.1554**	-0.0753	-0.0159
	(0.1818)	(0.0401)	(0.1549)	(0.0902)		(0.2044)	(0.0401)	(0.4602)	(0.0592)	(0.5507)	(0.0706)	(0.3793)	(0.0801)
Demographic2	0.0513	0.0116	-1.3568***	0.0814		0.4583**	0.0901**	0.2797	0.0359	-1.0884**	-0.1432**	-0.1579	-0.0333
	(0.2027)	(0.0457)	(0.1784)	(0.0969)		(0.2215)	(0.0431)	(0.4728)	(0.0606)	(0.5058)	(0.0661)	(0.3844)	(0.0811)
AdvMath			0.9118***	0.1320**				0.4780	0.0613	-0.0258	-0.0034	0.1268	0.0268
			(0.1212)	(0.0669)				(0.3239)	(0.0415)	(0.3566)	(0.0470)	(0.2574)	(0.0543)
ComScore				0.0112				0.0051	0.0007	0.1221	0.0161	0.0349	0.0074
				(0.0166)				(0.0676)	(0.0087)	(0.0787)	(0.0103)	(0.0579)	(0.0122)
YearTransMat						1.0061***	0.1977***						
						(0.1492)	(0.0264)						
$\ddot{m}_2$					1.0524***			-0.3224**	-0.0414**				
					(0.0003)			(0.1515)	(0.0192)				
$\overline{m_{2A}}$										-1.4912***	-0.1962***		
										(0.1656)	(0.0081)		
$\sqrt{\text{MeanSqError}}$			1.8530***	0.9790***	0.0041***								
			(0.0392)	(0.0022)	(0.0002)								
Obs | Pseudo-R^2	1000	0.3899											
LL | Param | AIC	-3656.6	52	7417.1										

Robust standard errors in parentheses: *p<0.10, **p<0.05, ***p<0.01.

Waitlist-Dynamic Unrestricted Estimates (Suboptimal)

A4: Full Waitlist-Dynamic Unrestricted Estimates (Optimal)

Table 30b: Waitlist-Dynamic Unrestricted Estimates (Optimal)

	FAdvMath		FComScore	F$\ddot{m}_2$	F$\overline{m_{2A}}$	Transition		Accept2		Accept3		Success	
	Coef	AME	Coef	Coef	Coef	Coef	AME	Coef	AME	Coef	AME	Coef	AME
Intercept	-6.4278***	-1.4433***	0.9765	5.5054***	-1.2247***	-7.8688***	-1.6527***	-5.4487**	-0.5308**	-0.1602	-0.0213	-10.4819***	-2.0411***
	(0.8383)	(0.1646)	(0.7368)	(0.3634)	(0.0038)	(0.9204)	(0.1634)	(2.3463)	(0.2269)	(2.0596)	(0.2735)	(1.8211)	(0.2882)
GREQuantPct	0.0732***	0.0164***	0.0564***	-0.0083*		0.0825***	0.0173***	0.0465	0.0045	0.0621**	0.0082**	0.1047***	0.0204***
	(0.0100)	(0.0020)	(0.0088)	(0.0045)		(0.0107)	(0.0020)	(0.0287)	(0.0028)	(0.0266)	(0.0034)	(0.0211)	(0.0035)
Gender	-0.0348	-0.0078	0.3118***	-0.0469		0.0553	0.0116	-0.5162	-0.0503	-0.1677	-0.0223	-0.0423	-0.0082
	(0.1373)	(0.0308)	(0.1188)	(0.0637)		(0.1410)	(0.0296)	(0.3697)	(0.0362)	(0.3034)	(0.0404)	(0.2493)	(0.0486)
Demographic1	0.6128***	0.1376***	-1.5764***	0.0091		-0.2800	-0.0588	0.2920	0.0284	0.4073	0.0541	-0.5056	-0.0984
	(0.1826)	(0.0401)	(0.1549)	(0.0902)		(0.1945)	(0.0407)	(0.6142)	(0.0600)	(0.4949)	(0.0654)	(0.3708)	(0.0716)
Demographic2	0.0632	0.0142	-1.3590***	0.0816		-0.0781	-0.0164	0.5062	0.0493	0.1398	0.0186	0.5141	0.1001
	(0.2037)	(0.0457)	(0.1784)	(0.0969)		(0.2140)	(0.0449)	(0.6069)	(0.0592)	(0.5084)	(0.0675)	(0.3855)	(0.0743)
AdvMath			0.9127***	0.1322**				0.3109	0.0303	-0.0573	-0.0076	-0.1314	-0.0256
			(0.1212)	(0.0669)				(0.3770)	(0.0367)	(0.3646)	(0.0484)	(0.2671)	(0.0520)
ComScore				0.0112				-0.0207	-0.0020	0.0648	0.0086	0.1494**	0.0291**
				(0.0166)				(0.0991)	(0.0096)	(0.0888)	(0.0118)	(0.0692)	(0.0133)
YearTransMat						0.7931***	0.1666***						
						(0.1403)	(0.0277)						
$\ddot{m}_2$					1.4277***			-0.1868	-0.0182				
					(0.0007)			(0.1655)	(0.0158)				
$\overline{m_{2A}}$										-1.0984***	-0.1459***		
										(0.1172)	(0.0034)		
$\sqrt{\text{MeanSqError}}$			1.8530***	0.9790***	0.0057***								
			(0.0392)	(0.0022)	(0.0005)								
Obs | Pseudo-R^2	1000	0.3770											
LL | Param | AIC	-3786.1	52	7676.3										

Robust standard errors in parentheses: *p<0.10, **p<0.05, ***p<0.01.

▸▸ Waitlist-Dynamic Unrestricted Estimates (Optimal)

A4: Waitlist-Hybrid Restricted Estimates (Suboptimal)

Table 31a: Waitlist-Hybrid Restricted Estimates (Suboptimal)

	$\overline{m_{2A}}$	$P(\text{Cutoff})_1$	$P(\text{Cutoff})_3$	Success 1	Success 3	Beta	Sigma
Year Transition/Matriculate Fewer | Intercept	0.1489***	32.92%	23.52%	-7.6626***	-3.1538**		
	(0.0018)	(27.79%, 38.50%)	(13.98%, 36.77%)	(1.7500)	(1.5900)		
GRE Quantitative Percentile				0.0803***	0.0283		
				(0.0206)	(0.0181)		
Gender				0.0907	-0.0455		
				(0.0878)	(0.1258)		
Demographic 1				-0.1575	-0.3403*		
				(0.1325)	(0.2031)		
Demographic 2				0.1673	-0.2274		
				(0.1341)	(0.2014)		
Advanced Math					0.1762		
					(0.1350)		
Committee Score					0.0376		
					(0.0304)		
Year Transition/Matriculate More		24.98%	70.26%				
		(22.60%, 27.52%)	(42.57%, 88.27%)				
$\ddot{m}_2$	1.0524***						
	(0.0003)						
Beta						0.6194***	
						(0.0889)	
Sigma							0.1589***
							(0.0526)
LR Statistic | DF | P-Value	48.5585	16	0.0000				

Waitlist-Dynamic Unrestricted Estimates (Suboptimal)

A4: Waitlist-Hybrid Restricted Estimates (Optimal)

Table 31b: Waitlist-Hybrid Restricted Estimates (Optimal)

	$\overline{m_{2A}}$	$P(\text{Cutoff})_1$	$P(\text{Cutoff})_3$	Success 1	Success 3	Beta	Sigma
Year Transition/Matriculate Fewer | Intercept	-1.2247***	37.56%	7.70%	-10.6778***	-9.8095***		
	(0.0038)	(32.38%, 43.04%)	(0.88%, 44.03%)	(1.4717)	(2.1222)		
GRE Quantitative Percentile				0.1193***	0.0978***		
				(0.0176)	(0.0239)		
Gender				-0.0260	-0.1737		
				(0.1189)	(0.1951)		
Demographic 1				-0.5947***	-0.2075		
				(0.1843)	(0.3184)		
Demographic 2				-0.0824	0.4580		
				(0.1758)	(0.2897)		
Advanced Math					-0.0104		
					(0.2250)		
Committee Score					0.1049*		
					(0.0570)		
Year Transition/Matriculate More		27.28%	95.10%				
		(23.97%, 30.86%)	(2.93%, 99.99%)				
$\ddot{m}_2$	1.4277***						
	(0.0007)						
Beta						0.9225***	
						(0.1209)	
Sigma							0.2832***
							(0.0617)
LR Statistic | DF | P-Value	13.3576	16	0.6465				

Waitlist-Dynamic Unrestricted Estimates (Optimal)

A4: Full Waitlist-Hybrid Restricted Estimates (Suboptimal)

Table 32a: Waitlist-Hybrid Restricted Estimates (Suboptimal)

	$F\overline{m_{2A}}$	Cutoff1	P(Cutoff)$_1$	Cutoff3	P(Cutoff)$_3$	Success1	Success3	Beta	Sigma
Intercept	0.1489***	-0.7116***	32.92%	-5.4270***	23.52%	-7.6626***	-3.1538**		
	(0.0018)	(0.1242)	(27.79%, 38.50%)	(1.9647)	(13.98%, 36.77%)	(1.7500)	(1.5900)		
GREQuantPct						0.0803***	0.0283		
						(0.0206)	(0.0181)		
Gender						0.0907	-0.0455		
						(0.0878)	(0.1258)		
Demographic1						-0.1575	-0.3403*		
						(0.1325)	(0.2031)		
Demographic2						0.1673	-0.2274		
						(0.1341)	(0.2014)		
AdvMath							0.1762		
							(0.1350)		
ComScore							0.0376		
							(0.0304)		
YearTransMat		-0.3883***	24.98%		70.26%				
		(0.1056)	(22.60%, 27.52%)		(42.57%, 88.27%)				
$\ddot{m}_2$	1.0524***								
	(0.0003)								
$\overline{m_{2A}}$				0.9855**					
				(0.3937)					
$\sqrt{\text{MeanSqError}}$	0.0041***								
	(0.0002)								
Beta								0.6194***	
								(0.0889)	
Sigma									0.1589***
									(0.0526)
Observations	1000								
LL | Param | AIC	-189.7	21	421.5						
LR Stat | DF | P-Val	48.5585	16	0.0000						

Robust standard errors in parentheses: *p<0.10, **p<0.05, ***p<0.01. Confidence intervals are 95%.

Waitlist-Dynamic Unrestricted Estimates (Suboptimal)

A4: Full Waitlist-Hybrid Restricted Estimates (Optimal)

Table 32b: Waitlist-Hybrid Restricted Estimates (Optimal)

	$F\overline{m_{2A}}$	Cutoff1	P(Cutoff)$_1$	Cutoff3	P(Cutoff)$_3$	Success1	Success3	Beta	Sigma
Intercept	-1.2247***	-0.5082***	37.56%	-11.0710	7.70%	-10.6778***	-9.8095***		
	(0.0038)	(0.1163)	(32.38%, 43.04%)	(7.1634)	(0.88%, 44.03%)	(1.4717)	(2.1222)		
GREQuantPct						0.1193***	0.0978***		
						(0.0176)	(0.0239)		
Gender						-0.0260	-0.1737		
						(0.1189)	(0.1951)		
Demographic1						-0.5947***	-0.2075		
						(0.1843)	(0.3184)		
Demographic2						-0.0824	0.4580		
						(0.1758)	(0.2897)		
AdvMath							-0.0104		
							(0.2250)		
ComScore							0.1049*		
							(0.0570)		
YearTransMat		-0.4722***	27.28%		95.10%				
		(0.1070)	(23.97%, 30.86%)		(2.93%, 99.99%)				
$\ddot{m}_2$	1.4277***								
	(0.0007)								
$\overline{m_{2A}}$				1.9422					
				(1.4272)					
$\sqrt{\text{MeanSqError}}$	0.0057***								
	(0.0005)								
Beta								0.9225***	
								(0.1209)	
Sigma									0.2832***
									(0.0617)
Observations	1000								
LL | Param | AIC	-275.0	21	592.0						
LR Stat | DF | P-Val	13.3576	16	0.6465						

Robust standard errors in parentheses: *p<0.10, **p<0.05, ***p<0.01. Confidence intervals are 95%.

Waitlist-Dynamic Unrestricted Estimates (Optimal)

A4: Waitlist-Hybrid Unrestricted Estimates (Suboptimal)

Table 33a: Waitlist-Hybrid Unrestricted Estimates (Suboptimal)

	F$\overline{m_{2A}}$	Transition		Accept2		Accept3		Success1		Success3	
	Coef	Coef	AME	Coef	AME	Coef	AME	Coef	AME	Coef	AME
Intercept	0.1489***	-10.7143***	-2.1065***	1.4111	0.1810	5.2706**	0.6876**	-7.5197***	-1.6198***	-7.8305***	-1.6644***
	(0.0018)	(1.0455)	(0.1549)	(2.3121)	(0.2948)	(2.3583)	(0.3035)	(0.9558)	(0.1909)	(1.7348)	(0.3277)
GREQuantPct		0.1111***	0.0218***	-0.0217	-0.0028	0.0304	0.0040	0.0810***	0.0175***	0.0802***	0.0171***
		(0.0119)	(0.0019)	(0.0253)	(0.0032)	(0.0266)	(0.0034)	(0.0113)	(0.0023)	(0.0206)	(0.0040)
Gender		0.3463**	0.0681**	0.3925	0.0503	-0.7569**	-0.0987**	-0.2071	-0.0446	-0.0143	-0.0030
		(0.1473)	(0.0286)	(0.2997)	(0.0386)	(0.3458)	(0.0441)	(0.1473)	(0.0314)	(0.2373)	(0.0504)
Demographic1		-0.2186	-0.0430	-0.1530	-0.0196	-1.1218**	-0.1463**	-0.2002	-0.0431	-0.1192	-0.0253
		(0.2038)	(0.0400)	(0.4589)	(0.0590)	(0.5553)	(0.0709)	(0.1986)	(0.0427)	(0.3732)	(0.0792)
Demographic2		0.4335**	0.0852**	0.2764	0.0355	-1.0364**	-0.1352**	-0.1484	-0.0320	-0.2127	-0.0452
		(0.2208)	(0.0431)	(0.4718)	(0.0604)	(0.5085)	(0.0661)	(0.2220)	(0.0477)	(0.3782)	(0.0803)
AdvMath				0.4911	0.0630	0.0415	0.0054			0.1456	0.0309
				(0.3246)	(0.0415)	(0.3585)	(0.0467)			(0.2555)	(0.0543)
ComScore				0.0047	0.0006	0.1279	0.0167			0.0319	0.0068
				(0.0677)	(0.0087)	(0.0788)	(0.0102)			(0.0577)	(0.0122)
YearTransMat		1.0063***	0.1979***								
		(0.1492)	(0.0265)								
$\ddot{m}_2$	1.0524***			-0.3346**	-0.0429**						
	(0.0003)			(0.1516)	(0.0192)						
$\overline{m_{2A}}$						-1.5313***	-0.1998***				
						(0.1683)	(0.0074)				
$\sqrt{\text{MeanSqError}}$	0.0041***										
	(0.0002)										
Obs | Pseudo-R^2	1000	0.9309									
LL | Param | AIC	-165.4	37	404.9								

Robust standard errors in parentheses: *p<0.10, **p<0.05, ***p<0.01.

Waitlist-Dynamic Unrestricted Estimates (Suboptimal)

A4: Waitlist-Hybrid Unrestricted Estimates (Optimal)

Table 33b: Waitlist-Hybrid Unrestricted Estimates (Optimal)

	F$\overline{m}_{2A}$	Transition		Accept2		Accept3		Success1		Success3	
	Coef	Coef	AME	Coef	AME	Coef	AME	Coef	AME	Coef	AME
Intercept	-1.2247***	-8.0729***	-1.6884***	-7.7449***	-0.7422***	-0.1816	-0.0241	-10.5573***	-2.1618***	-9.8892***	-1.9466***
	(0.0038)	(0.9326)	(0.1635)	(2.5864)	(0.2352)	(2.0599)	(0.2733)	(1.0083)	(0.1698)	(1.7557)	(0.2871)
GREQuantPct		0.0848***	0.0177***	0.0690**	0.0066**	0.0617**	0.0082**	0.1188***	0.0243***	0.0974***	0.0192***
		(0.0109)	(0.0020)	(0.0313)	(0.0029)	(0.0266)	(0.0034)	(0.0119)	(0.0020)	(0.0203)	(0.0035)
Gender		0.0593	0.0124	-0.5311	-0.0509	-0.1300	-0.0173	-0.0708	-0.0145	-0.0561	-0.0111
		(0.1415)	(0.0296)	(0.3773)	(0.0363)	(0.3031)	(0.0403)	(0.1494)	(0.0306)	(0.2465)	(0.0486)
Demographic1		-0.2873	-0.0601	0.2456	0.0235	0.4599	0.0610	-0.7173***	-0.1469***	-0.4344	-0.0855
		(0.1955)	(0.0407)	(0.6410)	(0.0617)	(0.4960)	(0.0653)	(0.2061)	(0.0414)	(0.3668)	(0.0718)
Demographic2		-0.0791	-0.0165	0.4982	0.0477	0.1980	0.0263	-0.0743	-0.0152	0.5745	0.1131
		(0.2150)	(0.0450)	(0.6312)	(0.0606)	(0.5096)	(0.0675)	(0.2199)	(0.0450)	(0.3821)	(0.0743)
AdvMath				0.2702	0.0259	-0.0617	-0.0082			-0.1088	-0.0214
				(0.3837)	(0.0367)	(0.3646)	(0.0484)			(0.2639)	(0.0520)
ComScore				-0.0175	-0.0017	0.0656	0.0087			0.1487**	0.0293**
				(0.0989)	(0.0095)	(0.0890)	(0.0118)			(0.0684)	(0.0133)
YearTransMat		0.8006***	0.1674***								
		(0.1410)	(0.0277)								
$\ddot{m}_2$	1.4277***			-0.1255	-0.0120						
	(0.0007)			(0.1679)	(0.0159)						
$\overline{m}_{2A}$						-1.1005***	-0.1461***				
						(0.1176)	(0.0034)				
$\sqrt{\text{MeanSqError}}$	0.0057***										
	(0.0005)										
Obs | Pseudo-R^2	1000	0.8919									
LL | Param | AIC	-268.3	37	610.6								

Robust standard errors in parentheses: *p<0.10, **p<0.05, ***p<0.01.

Waitlist-Dynamic Unrestricted Estimates (Optimal)

A4: Waitlist-Dynamic Restricted Estimates (Suboptimal)

Table 34a: Waitlist-Dynamic Restricted Estimates (Suboptimal)

	FAdvMath	FComScore	F$\ddot{m}_2$	F$\overline{m_{2A}}$	Cutoff1	L(Cutoff)$_1$	Cutoff3	P(Cutoff)$_3$	Success	Beta	Sigma
Intercept	-6.2714***	0.8833	5.4571***	0.1489***	0.3481***	1.4164	-15.2416***	13.00%	-8.5337*		
	(0.8340)	(0.7393)	(0.3633)	(0.0018)	(0.1172)	(1.1258, 1.7820)	(3.1088)	(3.20%, 40.28%)	(4.8648)		
GREQuantPct	0.0715***	0.0575***	-0.0076*						0.0886		
	(0.0099)	(0.0089)	(0.0045)						(0.0549)		
Gender	-0.0377	0.3141***	-0.0582						0.1445		
	(0.1366)	(0.1187)	(0.0637)						(0.2817)		
Demographic1	0.6097***	-1.5742***	0.0121						-0.4893*		
	(0.1817)	(0.1549)	(0.0902)						(0.2779)		
Demographic2	0.0603	-1.3544***	0.0733						-0.2386		
	(0.2024)	(0.1782)	(0.0969)						(0.3301)		
AdvMath		0.9105***	0.1148*						0.3908		
		(0.1212)	(0.0669)						(0.2501)		
ComScore			0.0124						0.0421		
			(0.0166)						(0.0642)		
YearTransMat					-0.2401***	1.1140		98.90%			
					(0.0613)	(0.9659, 1.2848)		(94.76%, 99.78%)			
$\ddot{m}_2$				1.0524***							
				(0.0003)							
$\overline{m_{2A}}$							3.0950***				
							(0.5798)				
$\sqrt{\text{MeanSqError}}$		1.8548***	0.9791***	0.0041***							
		(0.0394)	(0.0022)	(0.0002)							
Beta										0.9506***	
										(0.2236)	
Sigma											0.3633***
											(0.0992)
Observations	1000										
LL | Param | AIC	-3726.6	36	7525.3								
LR Stat | DF | P-Val	140.1329	16	0.0000								

Robust standard errors in parentheses: *p<0.10, **p<0.05, ***p<0.01. Confidence intervals are 95%.

Waitlist-Dynamic Unrestricted Estimates (Optimal)

A4: Waitlist-Dynamic Restricted Estimates (Optimal)

Table 34b: Waitlist-Dynamic Restricted Estimates (Optimal)

	FAdvMath	FComScore	F$\ddot{m}_2$	F$\overline{m_{2A}}$	Cutoff1	L(Cutoff)$_1$	Cutoff3	P(Cutoff)$_3$	Success	Beta	Sigma
Intercept	-6.3855***	0.8895	5.4674***	-1.2247***	0.2728***	1.3137	-10.8886***	8.54%	-10.6373***		
	(0.8428)	(0.7565)	(0.3635)	(0.0038)	(0.0348)	(1.2270, 1.4065)	(3.3289)	(0.78%, 52.65%)	(1.6709)		
GREQuantPct	0.0729***	0.0575***	-0.0080*						0.1086***		
	(0.0100)	(0.0091)	(0.0045)						(0.0189)		
Gender	-0.0394	0.3093***	-0.0477						-0.3655		
	(0.1370)	(0.1191)	(0.0637)						(0.2349)		
Demographic1	0.5960***	-1.5884***	0.0172						-0.2786		
	(0.1823)	(0.1549)	(0.0902)						(0.3409)		
Demographic2	0.0490	-1.3595***	0.0894						0.3797		
	(0.2034)	(0.1787)	(0.0969)						(0.3233)		
AdvMath		0.9255***	0.1356**						-0.1450		
		(0.1216)	(0.0669)						(0.3226)		
ComScore			0.0115						0.1492*		
			(0.0166)						(0.0862)		
YearTransMat					-0.1716***	1.1066		95.42%			
					(0.0352)	(1.0468, 1.1699)		(87.56%, 98.40%)			
$\ddot{m}_2$				1.4277***							
				(0.0007)							
$\overline{m_{2A}}$							1.9267***				
							(0.4829)				
$\sqrt{\text{MeanSqError}}$		1.8550***	0.9791***	0.0057***							
		(0.0393)	(0.0022)	(0.0005)							
Beta										0.9538***	
										(0.0337)	
Sigma											0.2945***
											(0.0281)
Observations	1000										
LL | Param | AIC	-3818.2	36	7708.3								
LR Stat | DF | P-Val	64.0402	16	0.0000								

Robust standard errors in parentheses: *p<0.10, **p<0.05, ***p<0.01. Confidence intervals are 95%.

Waitlist-Dynamic Unrestricted Estimates (Optimal)

A4: Waitlist-Dynamic Unrestricted Missing (Suboptimal)

Table 35a: Waitlist-Dynamic Unrestricted Missing (Suboptimal)

	FStage1		FAdvMath		FComScore	$F\acute{m}_2$	$F\overline{m_{2A}}$	Transition		Accept2		Accept3		Success	
	Coef	AME	Coef	AME	Coef	Coef	Coef	Coef	AME	Coef	AME	Coef	AME	Coef	AME
Intercept	-6.3804***	-2.0906***	-3.4981*	-1.2239*	2.8114	7.2395***	0.3539***	-10.7082***	-2.1055***	1.3743	0.1762	5.3172**	0.6942**	-7.8194***	-1.6624***
	(0.6106)	(0.1572)	(1.8860)	(0.6473)	(2.6732)	(0.6887)	(0.0038)	(1.0451)	(0.1549)	(2.2965)	(0.2928)	(2.3592)	(0.3037)	(1.7334)	(0.3276)
GREQuantPct	0.0661***	0.0217***	0.0396**	0.0139**	0.0394	-0.0260***		0.1110***	0.0218***	-0.0219	-0.0028	0.0295	0.0038	0.0799***	0.0170***
	(0.0070)	(0.0019)	(0.0184)	(0.0063)	(0.0258)	(0.0083)		(0.0119)	(0.0019)	(0.0253)	(0.0032)	(0.0266)	(0.0034)	(0.0206)	(0.0040)
Gender	0.2030**	0.0665**	0.1626	0.0569	0.6119***	-0.2034**		0.3464**	0.0681**	0.3963	0.0508	-0.7544**	-0.0985**	-0.0159	-0.0034
	(0.0880)	(0.0286)	(0.1475)	(0.0513)	(0.2188)	(0.1028)		(0.1473)	(0.0286)	(0.2997)	(0.0386)	(0.3455)	(0.0441)	(0.2373)	(0.0504)
Demographic1	-0.1332	-0.0437	0.6245***	0.2185***	-1.2588***	0.0513		-0.2141	-0.0421	-0.1504	-0.0193	-1.0906**	-0.1424**	-0.0979	-0.0208
	(0.1213)	(0.0396)	(0.2084)	(0.0703)	(0.2771)	(0.1586)		(0.2039)	(0.0400)	(0.4588)	(0.0589)	(0.5549)	(0.0711)	(0.3742)	(0.0795)
Demographic2	0.2572*	0.0843*	0.0475	0.0166	-1.2957***	-0.0137		0.4383**	0.0862**	0.2732	0.0350	-1.0075**	-0.1315**	-0.1905	-0.0405
	(0.1321)	(0.0430)	(0.2234)	(0.0781)	(0.3259)	(0.1620)		(0.2209)	(0.0431)	(0.4721)	(0.0604)	(0.5084)	(0.0663)	(0.3793)	(0.0805)
AdvMath					0.7506***	0.0656				0.4923	0.0631	0.0398	0.0052	0.1438	0.0306
					(0.2176)	(0.1073)				(0.3247)	(0.0415)	(0.3583)	(0.0467)	(0.2554)	(0.0543)
ComScore						0.0369				0.0048	0.0006	0.1290	0.0168*	0.0328	0.0070
						(0.0261)				(0.0678)	(0.0087)	(0.0788)	(0.0102)	(0.0577)	(0.0122)
YearTransMat	0.5997***	0.1965***						1.0061***	0.1978***						
	(0.0885)	(0.0266)						(0.1491)	(0.0264)						
$\acute{m}_2$							1.0263***			-0.3288**	-0.0422**				
							(0.0007)			(0.1479)	(0.0187)				
$\overline{m_{2A}}$												-1.5304***	-0.1998***		
												(0.1678)	(0.0074)		
InvMills			-0.2289	-0.0801	-0.7304										
			(0.3545)	(0.1241)	(0.5361)										
$\sqrt{\text{MeanSqError}}$					1.8994***	0.9581***	0.0112***								
					(0.0682)	(0.0145)	(0.0005)								
Obs | Pseudo-R^2	1000	0.4934													
LL | Param | AIC	-2023.1	60	4166.3												

Robust standard errors in parentheses: *p<0.10, **p<0.05, ***p<0.01.

Waitlist-Dynamic Unrestricted Estimates (Suboptimal)

A4: Waitlist-Dynamic Unrestricted Missing (Optimal)

Table 35b: Waitlist-Dynamic Unrestricted Missing (Optimal)

	FStage1		FAdvMath		FComScore	F$\ddot{m}_2$	F$\overline{m_{2A}}$	Transition		Accept2		Accept3		Success	
	Coef	AME	Coef	AME	Coef	Coef	Coef	Coef	AME	Coef	AME	Coef	AME	Coef	AME
Intercept	-4.8625***	-1.6784***	-3.3658*	-1.1857*	1.8384	6.2905***	-0.3093***	-8.0678***	-1.6875***	-7.7385***	-0.7415***	-0.1808	-0.0240	-9.8861***	-1.9462***
	(0.5540)	(0.1650)	(1.8728)	(0.6491)	(2.4312)	(0.7189)	(0.0043)	(0.9324)	(0.1635)	(2.5841)	(0.2347)	(2.0591)	(0.2734)	(1.7554)	(0.2871)
GREQuantPct	0.0510***	0.0176***	0.0419**	0.0148**	0.0420*	-0.0174**		0.0848***	0.0177***	0.0682**	0.0065**	0.0620**	0.0082**	0.0976***	0.0192***
	(0.0065)	(0.0020)	(0.0177)	(0.0061)	(0.0231)	(0.0086)		(0.0109)	(0.0020)	(0.0312)	(0.0029)	(0.0266)	(0.0034)	(0.0203)	(0.0035)
Gender	0.0357	0.0123	0.0639	0.0225	0.2914	0.0890		0.0591	0.0124	-0.5395	-0.0517	-0.1356	-0.0180	-0.0596	-0.0117
	(0.0858)	(0.0296)	(0.1456)	(0.0513)	(0.1923)	(0.1128)		(0.1415)	(0.0296)	(0.3783)	(0.0364)	(0.3031)	(0.0403)	(0.2466)	(0.0486)
Demographic1	-0.1721	-0.0594	0.4192**	0.1477**	-1.1334***	0.1101		-0.2879	-0.0602	0.2533	0.0243	0.4261	0.0566	-0.4539	-0.0894
	(0.1174)	(0.0404)	(0.1970)	(0.0683)	(0.2557)	(0.1627)		(0.1955)	(0.0407)	(0.6433)	(0.0619)	(0.4952)	(0.0654)	(0.3662)	(0.0716)
Demographic2	-0.0380	-0.0131	-0.0492	-0.0173	-0.8501***	0.1106		-0.0799	-0.0167	0.5085	0.0487	0.1735	0.0230	0.5555	0.1093
	(0.1294)	(0.0446)	(0.2143)	(0.0755)	(0.2867)	(0.1773)		(0.2150)	(0.0449)	(0.6333)	(0.0608)	(0.5088)	(0.0675)	(0.3812)	(0.0742)
AdvMath					1.0421***	0.1118				0.2795	0.0268	-0.0581	-0.0077	-0.1045	-0.0206
					(0.1961)	(0.1240)				(0.3842)	(0.0368)	(0.3645)	(0.0484)	(0.2639)	(0.0520)
ComScore						0.0053				-0.0174	-0.0017	0.0645	0.0086	0.1478**	0.0291**
						(0.0312)				(0.0989)	(0.0095)	(0.0889)	(0.0118)	(0.0684)	(0.0133)
YearTransMat	0.4862***	0.1678***						0.8004***	0.1674***						
	(0.0847)	(0.0277)						(0.1410)	(0.0277)						
$\ddot{m}_2$							1.2910***			-0.1179	-0.0113				
							(0.0008)			(0.1517)	(0.0144)				
$\overline{m_{2A}}$												-1.0993***	-0.1460***		
												(0.1173)	(0.0034)		
InvMills			-0.3619	-0.1275	-0.0012										
			(0.4395)	(0.1545)	(0.5745)										
$\sqrt{\text{MeanSqError}}$					1.7743***	1.0532***	0.0145***								
					(0.0631)	(0.0129)	(0.0006)								
Obs | Pseudo-R^2	1000	0.4716													
LL | Param | AIC	-2143.9	60	4407.8												

Robust standard errors in parentheses: *p<0.10, **p<0.05, ***p<0.01.

Waitlist-Dynamic Unrestricted Estimates (Optimal)

A4: Waitlist-Dynamic Restricted Missing (Suboptimal)

Table 36a: Waitlist-Dynamic Restricted Missing (Suboptimal)

	FStage1	FAdvMath	FComScore	F$\ddot{m}_2$	F$\overline{m_{2A}}$	Cutoff1	L(Cutoff)$_1$	Cutoff3	P(Cutoff)$_3$	Success	Beta	Sigma
Intercept	-6.3854***	-3.4955*	2.8010	7.1897***	0.3539***	0.3447	1.4115	-15.2825**	12.63%	-8.1530		
	(0.6222)	(1.8891)	(2.7427)	(0.6891)	(0.0038)	(0.2369)	(0.8873, 2.2456)	(6.4479)	(1.76%, 53.89%)	(7.7494)		
GREQuantPct	0.0662***	0.0397**	0.0402	-0.0254***						0.0841		
	(0.0071)	(0.0185)	(0.0265)	(0.0083)						(0.0876)		
Gender	0.2028**	0.1634	0.6180***	-0.2247**						0.1718		
	(0.0882)	(0.1475)	(0.2190)	(0.1027)						(0.3545)		
Demographic1	-0.1360	0.6339***	-1.2499***	0.0656						-0.4460		
	(0.1214)	(0.2084)	(0.2776)	(0.1587)						(0.2837)		
Demographic2	0.2547*	0.0562	-1.2917***	-0.0198						-0.2234		
	(0.1322)	(0.2229)	(0.3267)	(0.1621)						(0.3332)		
AdvMath			0.7526***	0.0283						0.2449		
			(0.2176)	(0.1074)						(0.2493)		
ComScore				0.0398						0.0517		
				(0.0261)						(0.0637)		
YearTransMat	0.6046***					-0.2388**	1.1117		98.87%			
	(0.0900)					(0.1113)	(0.8544, 1.4464)		(70.77%, 99.97%)			
$\ddot{m}_2$					1.0263***							
					(0.0007)							
$\overline{m_{2A}}$								3.0968**				
								(1.2801)				
InvMills		-0.2419	-0.7991									
		(0.3534)	(0.5481)									
$\sqrt{\text{MeanSqError}}$			1.9101***	0.9584***	0.0112***							
			(0.0695)	(0.0145)	(0.0005)							
Beta											0.9496***	
											(0.0051)	
Sigma												0.3621*
												(0.2142)
Observations	1000											
LL | Param | AIC	-2093.9	44	4275.8									
LR Stat | DF | P-Val	141.5488	16	0.0000									

Robust standard errors in parentheses: *p<0.10, **p<0.05, ***p<0.01. Confidence intervals are 95%.

Waitlist-Dynamic Unrestricted Estimates (Suboptimal)

A4: Waitlist-Dynamic Restricted Missing (Optimal)

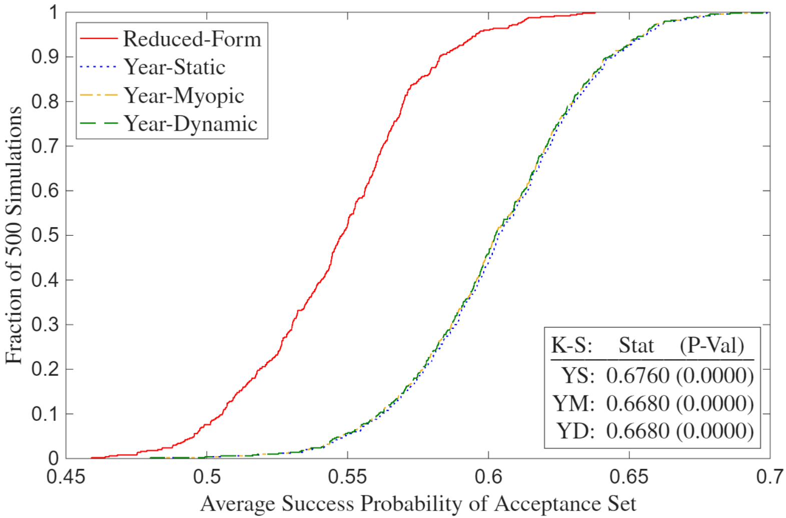
Table 36b: Waitlist-Dynamic Restricted Missing (Optimal)

	FStage1	FAdvMath	FComScore	F$\dot{m}_2$	F$\overline{m_{2A}}$	Cutoff1	L(Cutoff)$_1$	Cutoff3	P(Cutoff)$_3$	Success	Beta	Sigma
Intercept	-4.8616***	-3.3608*	1.8102	6.2650***	-0.3093***	0.2697***	1.3096	-10.5162***	9.90%	-10.1044***		
	(0.5602)	(1.8772)	(2.4663)	(0.7187)	(0.0043)	(0.0343)	(1.2245, 1.4005)	(2.4227)	(1.81%, 39.53%)	(1.7608)		
GREQuantPct	0.0510***	0.0420**	0.0439*	-0.0171**						0.1033***		
	(0.0065)	(0.0177)	(0.0235)	(0.0086)						(0.0203)		
Gender	0.0360	0.0631	0.2795	0.0906						-0.3537		
	(0.0858)	(0.1459)	(0.1928)	(0.1128)						(0.2316)		
Demographic1	-0.1719	0.4208**	-1.1529***	0.1064						-0.2621		
	(0.1174)	(0.1973)	(0.2563)	(0.1627)						(0.3374)		
Demographic2	-0.0379	-0.0463	-0.8508***	0.1103						0.3731		
	(0.1294)	(0.2148)	(0.2883)	(0.1773)						(0.3240)		
AdvMath			1.0446***	0.1079						-0.1879		
			(0.1986)	(0.1240)						(0.3391)		
ComScore				0.0055						0.1416*		
				(0.0312)						(0.0826)		
YearTransMat	0.4856***					-0.1701***	1.1047		95.54%			
	(0.0851)					(0.0347)	(1.0451, 1.1677)		(86.61%, 98.61%)			
$\dot{m}_2$					1.2910***							
					(0.0008)							
$\overline{m_{2A}}$								1.8792***				
								(0.3680)				
InvMills		-0.3751	-0.1080									
		(0.4435)	(0.5806)									
$\sqrt{\text{MeanSqError}}$			1.7658***	1.0534***	0.0145***							
			(0.0622)	(0.0129)	(0.0006)							
Beta											0.9513***	
											(0.0058)	
Sigma												0.2923***
												(0.0262)
Observations	1000											
LL | Param | AIC	-2177.3	44	4442.5									
LR Stat | DF | P-Val	66.7052	16	0.0000									

Robust standard errors in parentheses: *p<0.10, **p<0.05, ***p<0.01. Confidence intervals are 95%.

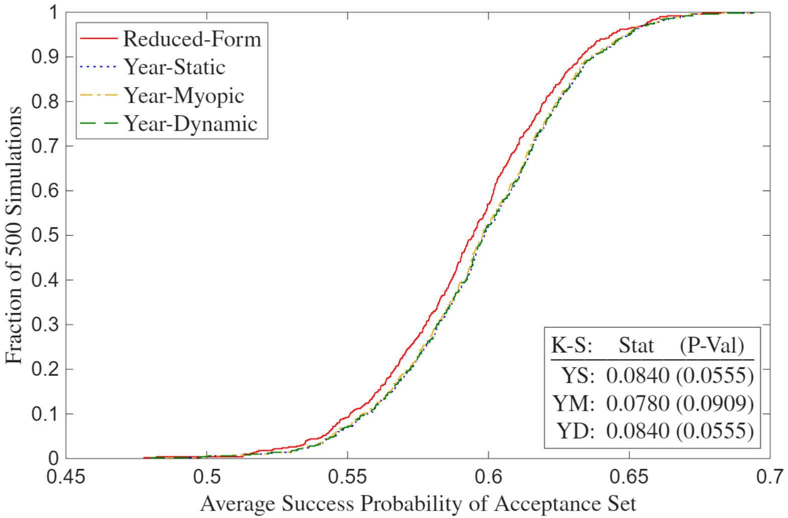
Waitlist-Dynamic Unrestricted Estimates (Optimal)

A4: Full Deviation Gains (Suboptimal)



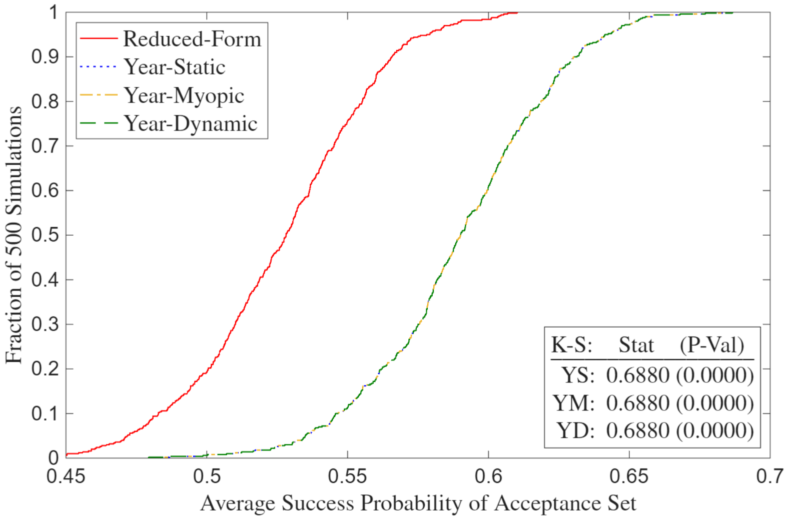
▸▸ Highlighted Deviation Gains (Suboptimal)

A4: Full Deviation Gains (Suboptimal)



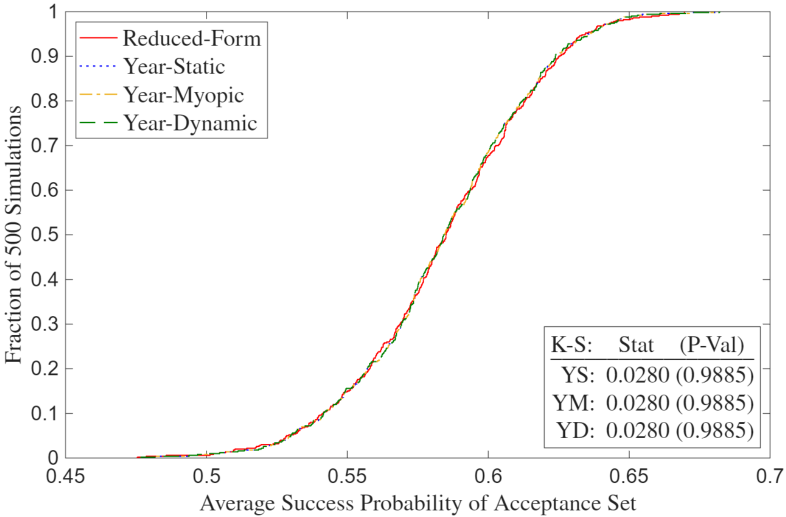
▸▸ Highlighted Deviation Gains (Optimal)

A4: Deviation Gains Missing (Suboptimal)



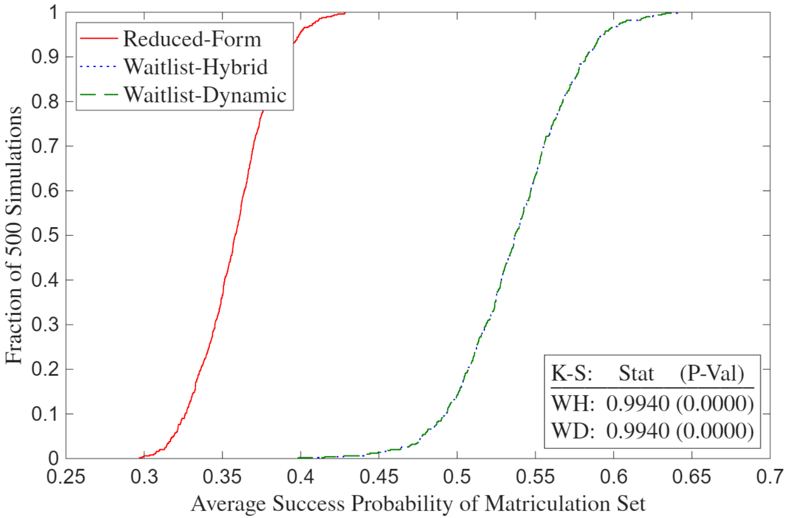
Deviation Gains (Suboptimal)

A4: Deviation Gains Missing (Optimal)



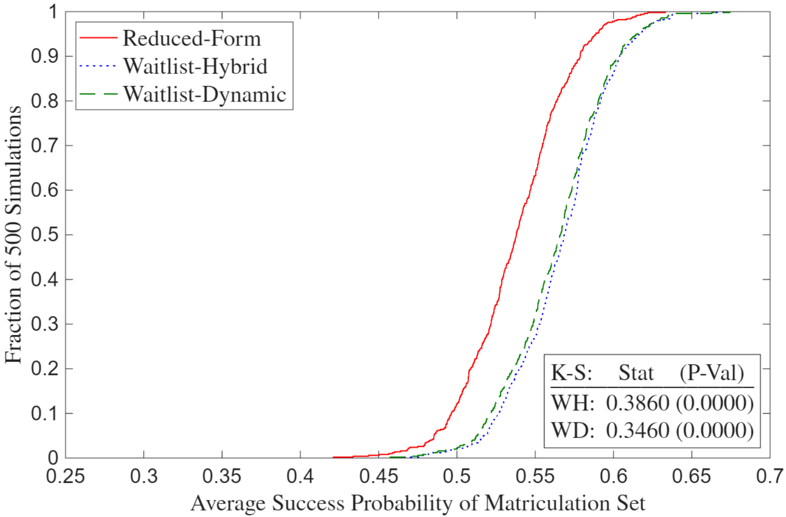
Deviation Gains (Optimal)

A4: Full Waitlist Deviation Gains (Suboptimal)



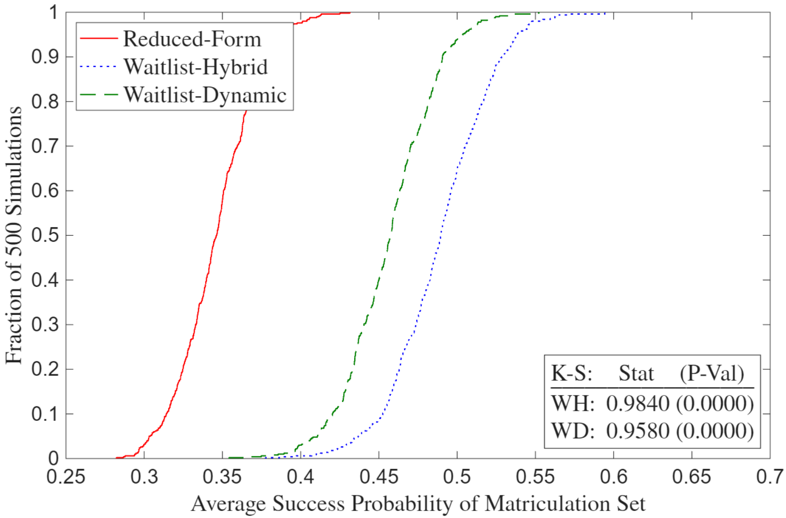
Highlighted Waitlist Deviation Gains (Suboptimal)

A4: Full Waitlist Deviation Gains (Optimal)



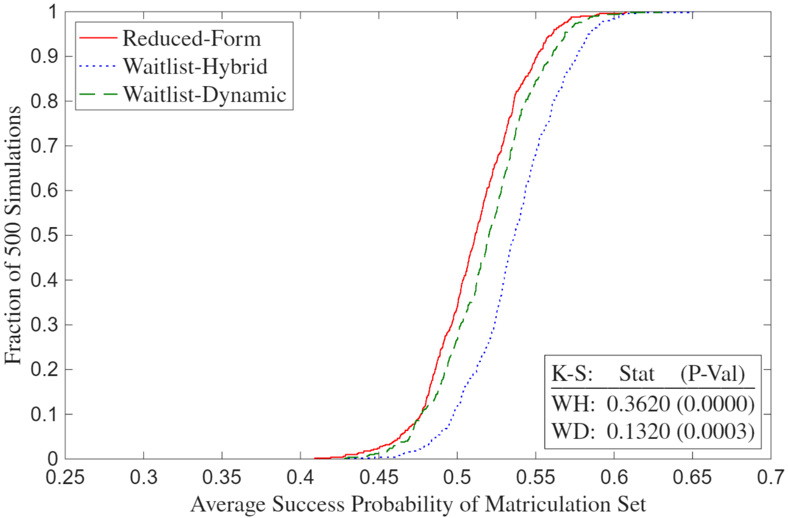
Highlighted Waitlist Deviation Gains (Optimal)

A4: Waitlist Deviation Gains Missing (Suboptimal)



Waitlist Deviation Gains (Suboptimal)

A4: Waitlist Deviation Gains Missing (Optimal)



Waitlist Deviation Gains (Optimal)

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