Catch up, Mismatch and Learning: Some Evidence from India and Turkey

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Motivation

- Affirmative action (AA) policies used to advance disadvantaged
- In India, reservations for SC/ST/OBC
- In US, AA or 10% rules
- Intense debate over impact of such policies
- Shift from race-based to economic-based AA has been suggested

Plan

- Work on AA
- India: Targeting, Catchup and Mismatch in an EEI
  - Data
  - Results
- Work on Learning
- Turkey: Learning among repeat takers
  - Data
  - Results
- Implications for policy

US Background

- Supreme Court to rule on this in September 2012
  - Fisher vs. University of Texas
  - Texas top 10 percent law response to 1996 ruling banning affirmative action in Texas' public universities.
  - In 2003, U.S. Supreme Court approved "points" for diverse student body. In response, the UT reinstated affirmative action on top of 10 percent law. Abigail Noel Fisher was denied admission and is white.

Work on Affirmative Action in US

- Rothstein and Yoon's (2008, 2009): Find better school, lower graduation and bar passage rates for black students in the lowest quintile of admission credentials.
- Sander (2004); Average performance gap between blacks and whites at selective law schools is large and gets *larger* over years, lower probability of graduation, mostly due to reduced grades.

Work on Affirmative Action In US

- THEOP (Texas Higher Education Opportunity Project)
  - Top 10% public high schools in Texas are automatically granted admission to the University of Texas
  - Alon and Tienda (2005): Higher graduation rates, GPAs for those admitted under 10% rule. Niu and Tienda (2011), (2012): High school GPA better predicts college performance measured by GPA than performance in standardized tests.
  - Do not control for the difficulty of the courses taken.
  - If those admitted under the 10% rule take easy courses they may be more likely to graduate and get better GPAs, which need not imply better performance or outcomes.

Work on Affirmative Action in US

- Arcidiacono et al. (2011): Shows that although the GPA gap between white and black students at Duke University falls by half between the first and the last year of college, this comes primarily from smaller variance in grading during later years and a higher proportion of black students switching into easier majors

Work on Affirmative Action in India

- Bertrand et al. (2010) follow a pool of applicants to Indian engineering colleges in 1996 in one state in India
  - Targeting exists as general displaced students richer than SC/ST displacing ones
  - Evidence against strong mismatch: wage increase after attending engineering college
  - But gains displacing $<$ losses displaced
  - Problems: no grades

Our Work on Affirmative Action in India

- We use data on class from an EEI in India
- Fertile ground to evaluate AA policies
  - Transparent admission criteria, extreme preferences, rigid course structure
  - Reservations: SC/ST take the JEE with general students but 15% and 7.5% of the seats in *each major* are reserved for SC and ST students, respectively.
  - Extreme: 97% (GE) vs 50% (SC/ST) and not able to fill.
  - Thus, gap between SC/ST and their non minority peers is greater in selective majors

Main Finding

- **Targeting:** AA effectively targets SC/ST students who are poorer than average displaced

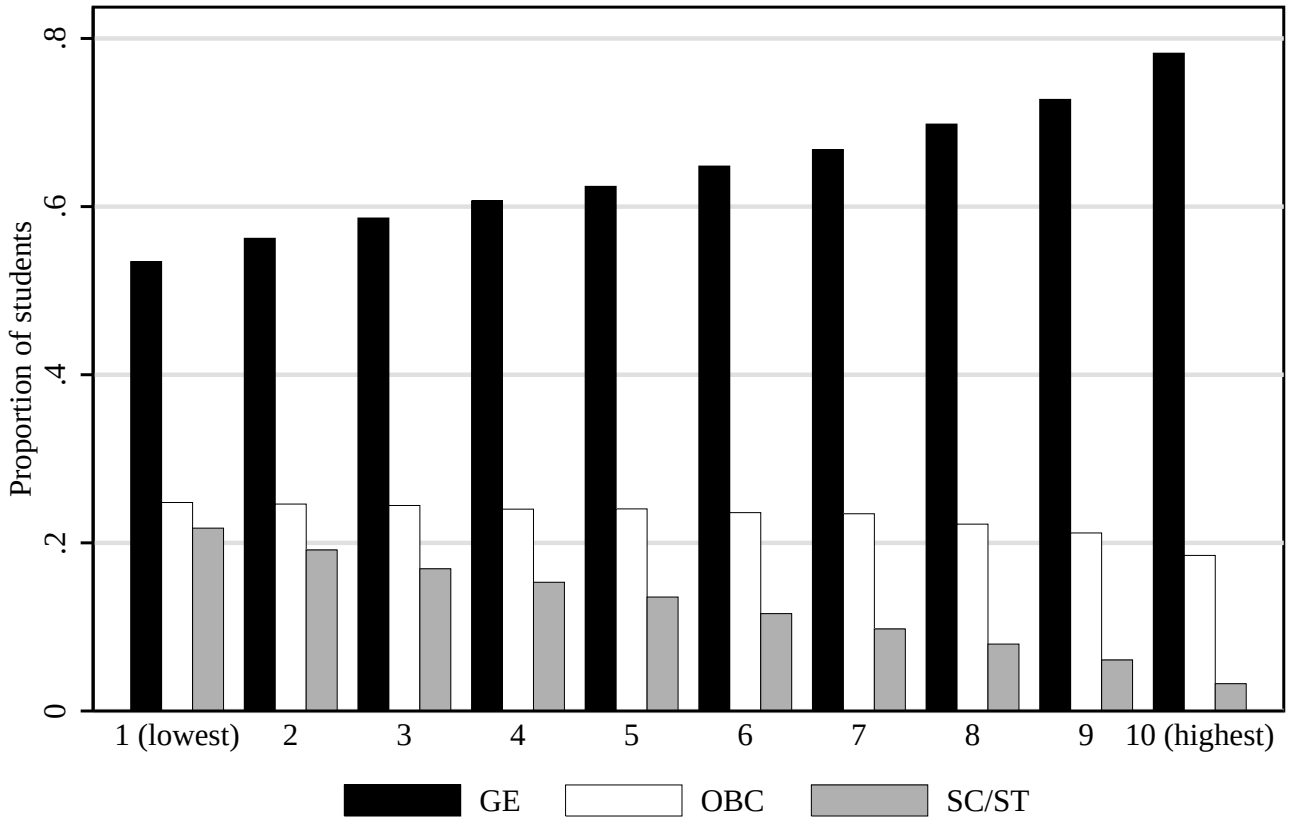
general student

- **Catchup**: SC/ST students, *fall behind* their same-major peers, more so in selective majors
- **Mismatch:** SC/ST students in more selective majors earn less than if they would have earned in less selective majors. They also experience higher stress levels and feelings of not belonging.

Main Finding

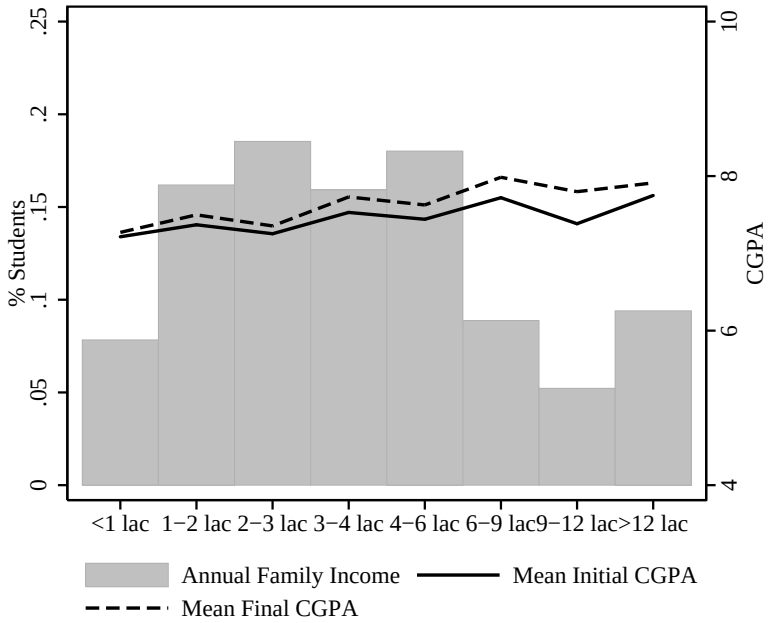
- 453 students graduating in 2008. 356 Bachelor and 97 Dual Degree/Integrated Master
- Three sources of data:
  - Institutional records: GPA and credits by semester, gender, caste, age, and major.
  - Exit survey: schooling, parents' education, family income, first wage after graduation, among others.
  - JEE applicant data 2009: 384,977 applicants for 8295 seats
- Limitations:
  - No data on JEE scores: We use first year CGPA
  - Missing data: Multiple random imputation methods
  - No data on applicants

Results: Initial Credentials

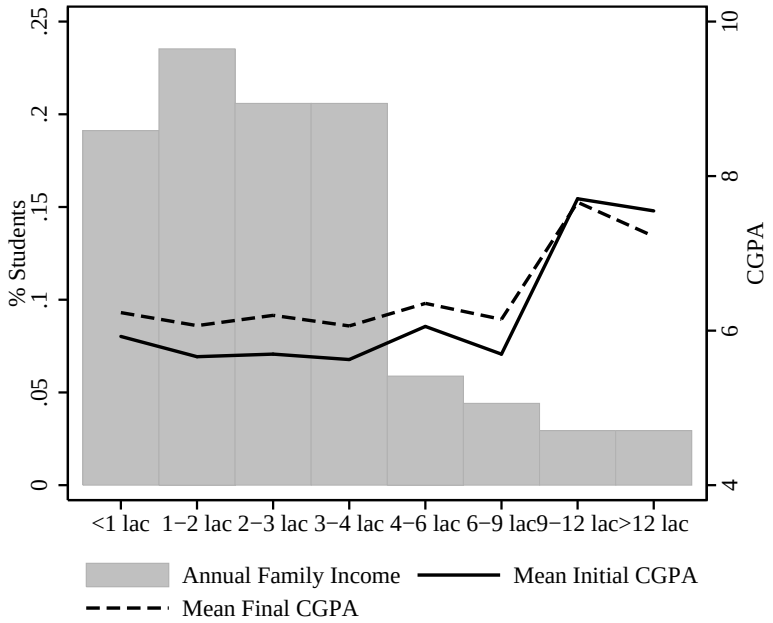


- Displacing minority students come from poorer districts than displaced general students
- SC/ST Worst prepared

Results: Caste, Income, Performance



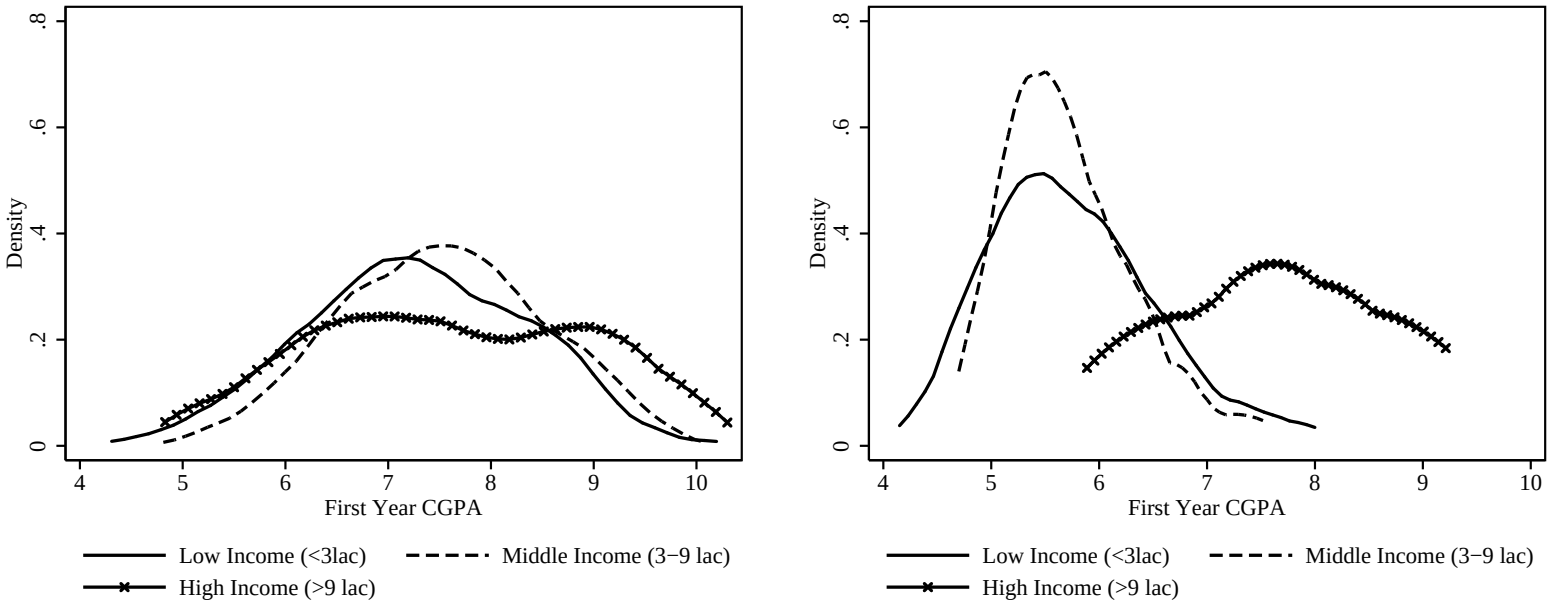
(a) General Category



(b) SC/ST

- Income, grades and caste:
  - For GE, income and grades slightly positively correlated.
  - For SC/ST: rich SC/ST look like GE.

Targeting

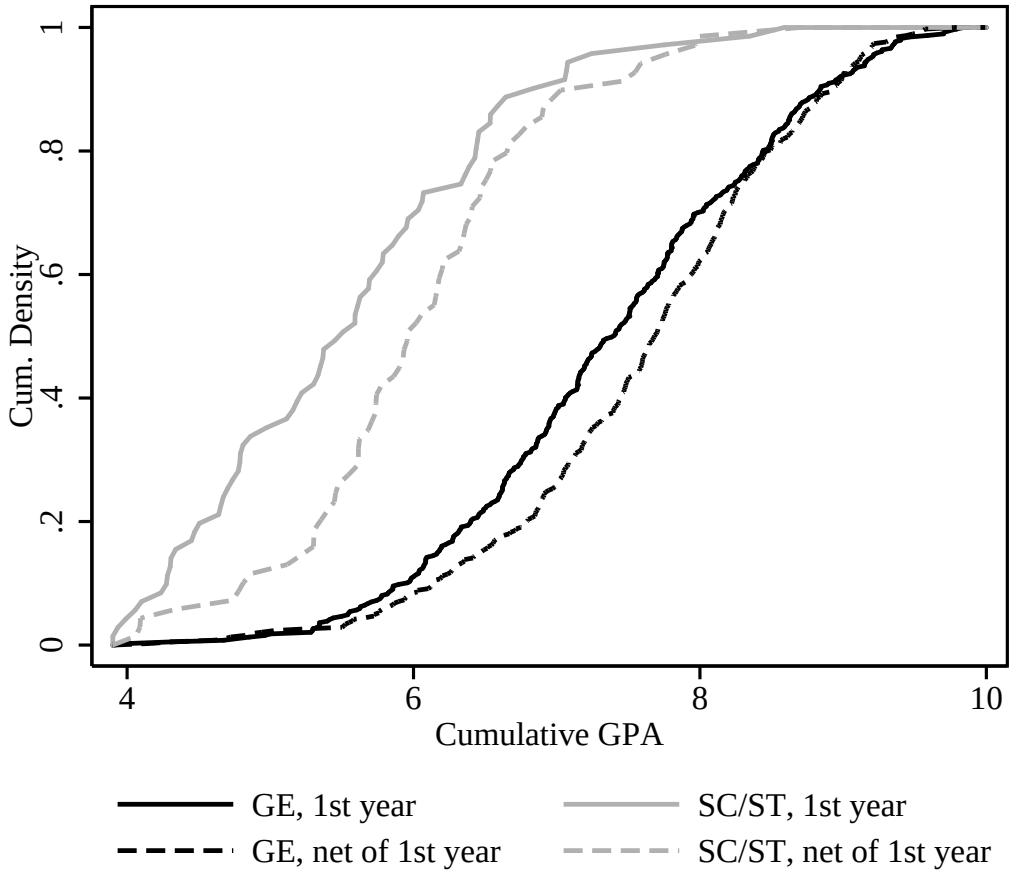


(a) General Category

(b) SC/ST

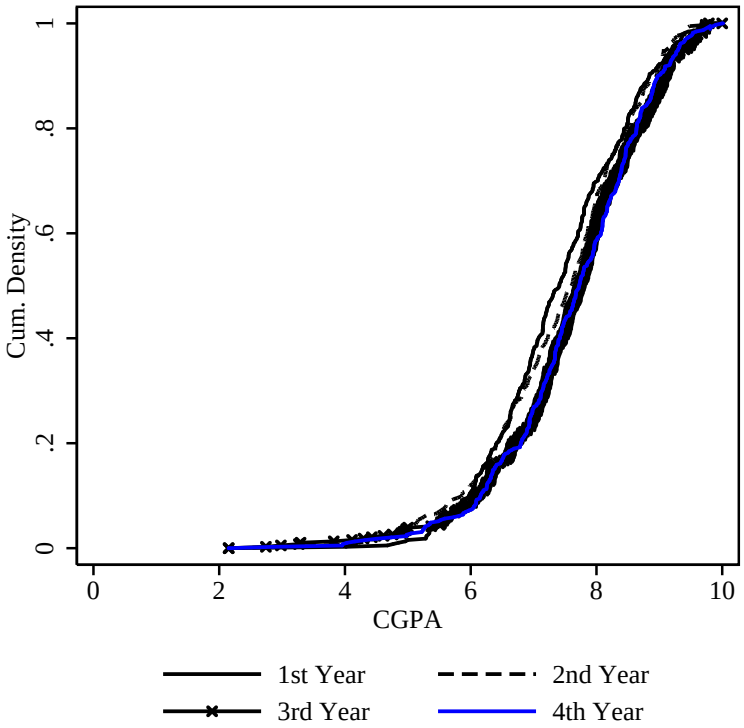
- Creamy layer not an issue: few rich and look like GE

Catch Up?

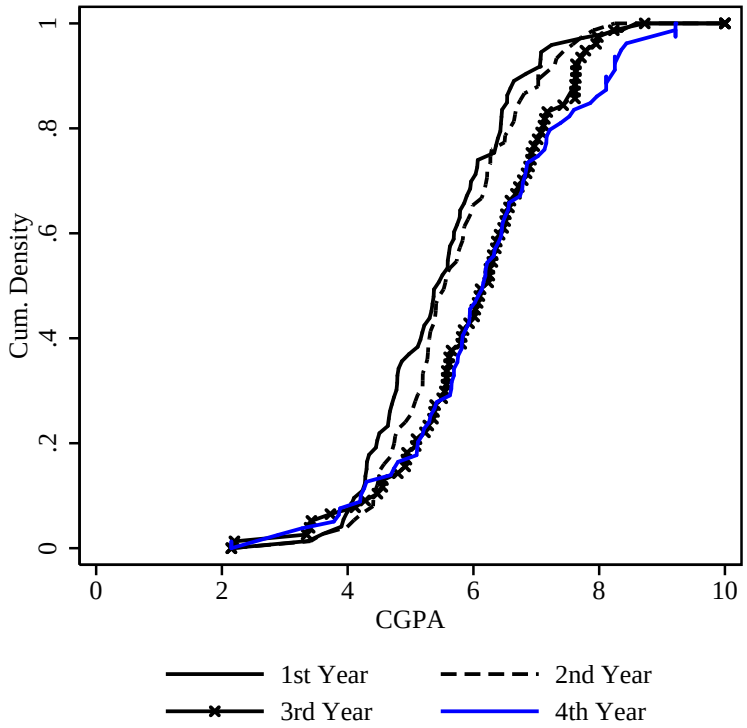


- Catchup: Gap in average CGPA between general and SC/ST students shrinks by 15%
- Grading differs by major?

Catch Up?



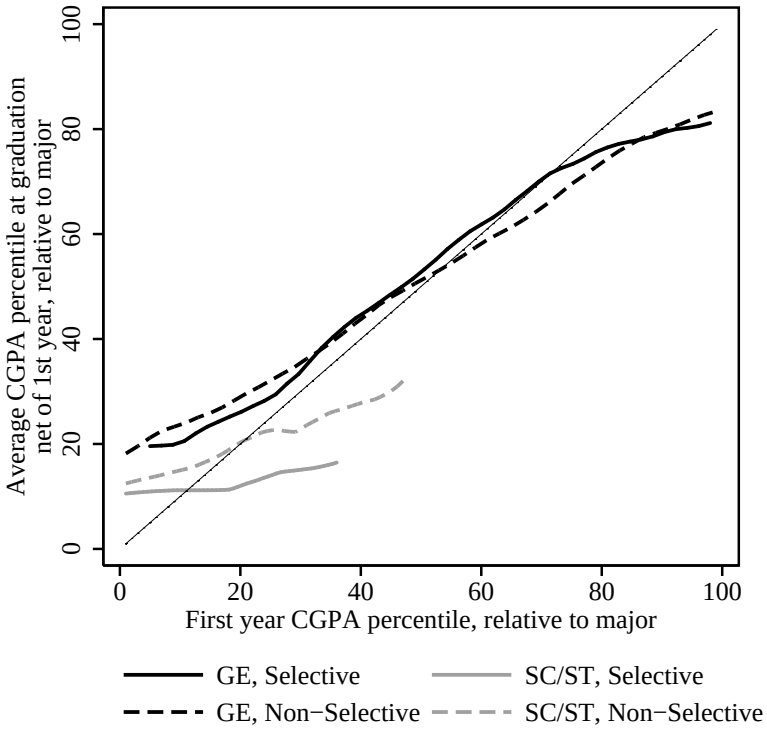
(a) GE



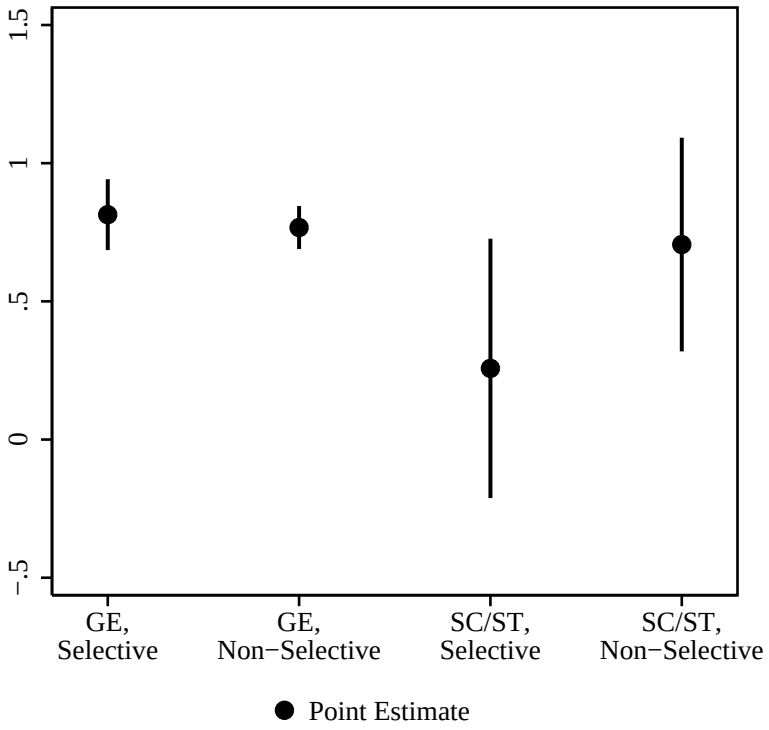
(b) SC/ST

- Distribution of grades for SC/ST students “improves” over time

Results Catch Up



(a)



(b)

- Grades relative to the major
  - Flatter curves for SC/ST, more so in selective majors
  - Falling behind, not catching up

Labor Market Outcomes and Majors

- Do SC/ST gain in wages from going to selective majors?
- Interval regression of wages on being in a selective major and X.
- Let w_i^* denote individual i's wage at graduation:

$$w_i^* = \alpha_1 S_i + X_i \beta_1 - \epsilon_i$$

  where $w_i = W_k$ if $\xi_{k-1} \leq w_i^* \leq \xi_k$
- If $\alpha_1 \leq 0$, better off in less selective major: mismatch.
- Better students in selective majors: need to control for selection
- PSM: Control for observables in selection
- But what about unobservables?

Labor Market Outcomes and Majors

- Joint estimation of selection and earnings: correlation in errors captures unobservables
- Model is represented by the system:

$$\begin{aligned} \Pr(w_i = W_k | X_i) &= \Phi(\alpha_1 S_i + X_i\beta_1 - \xi_{k-1}; \sigma_\epsilon^2) \\ &\quad -\Phi(\alpha_1 S_i + X_i\beta_1 - \xi_k; \sigma_\epsilon^2) \\ \Pr(S = 1 | Z_i) &= \Phi(Z_i\gamma; \sigma_\mu^2) \end{aligned}$$

where X_i denotes observed individual characteristics and Z_i contains X_i.

Labor Market Outcomes and Majors

- Run probit on being in selective major
  - Let S_i^* be a latent continuous variable representing selectivity of i's major:

$$S_i^* = Z_i\gamma - \mu_i$$

    where $S_i = 1$ if $S_i^* > 0$ and $S_i = 0$ if $S_i^* < 0$.
- Then run interval regression for wages
- Let w_i^* denote individual i's wage at graduation:

$$w_i^* = \alpha_1 S_i + X_i\beta_1 - \epsilon_i$$

  where $w_i = W_k$ if $\xi_{k-1} \leq w_i^* \leq \xi_k$
- If $\alpha_1 \leq 0$, better off in less selective major: mismatch

Mismatch: Results

Table: Effect of Attending a Selective Major at EEI on Wages ($\hat{\alpha}_1$)

	Interval Regression	PS	Joint Estimation
GE	0.185***	0.176***	0.115
	(0.036)	(0.037)	(0.149)
			ρ = 0.196
SC/ST	0.055	-0.001	-0.380*
	(0.085)	(0.093)	(0.199)
			ρ = 0.913

- Estimates fall as Control for observables (PSM) and unobservables (JE).

Social Mismatch

- Let y_i denote an aspect of individual i's well being, stress, so positive coefficient is bad...:

$$y_i^* = \alpha_2 S_i + X_i \beta_2 - v_i$$

  where $y_i = 1$ if $y_i^* > 0$ and $y_i = 0$ if $y_i^* < 0$.

- Now, the system becomes:

$$\begin{aligned} \Pr(y_i = 1 | X_i) &= \Phi(\alpha_2 S_i + X_i \beta_2; \sigma_v^2) \\ \Pr(S = 1 | Z_i) &= \Phi(Z_i \gamma; \sigma_\mu^2) \end{aligned}$$

- If $\alpha_2 \geq 0$, more stress from being in selective major. Mismatch.
- Negative for GE, positive for SC/ST.
- $\rho > 0$, Type A personalities, stressed out people, choose more selective majors

Mismatch: Social Mismatch: Results

Table: Effect of Attending a Selective Major at EEI on Emotional and Social Well-Being ($\hat{\alpha}_2$)

	Probit	PS	Joint Estimation
Stress			
GE	0.112*	0.125*	-0.082***
	(0.065)	(0.068)	(0.010)
			ρ=0.85
SC/ST	0.351***	0.320**	0.115**
	(0.120)	(0.137)	(0.046)
			ρ= -0.34
Hostel feels like home			
GE	0.005	0.008	0.014
	(0.056)	(0.058)	(0.099)
			ρ = -0.09
SC/ST	-0.159	-0.088	-0.103**
	(0.118)	(0.125)	(0.052)
			ρ=0.78

Summary

- Evidence falling behind, labor market mismatch, and social mismatch.
- Suggests such extreme preferences may not even be in the interest of SC/ST

Looking for Catchup

- Through the Looking-Glass-By Lewis Caroll :

”Well, in our country,” said Alice, still panting a little, ”you’d generally get to somewhere else — if you run very fast for a long time, as we’ve been doing.”
”A slow sort of country!” said the Queen. ”Now, here, you see, it takes all the running you can do, to keep in the same place. If you want to get somewhere else, you must run at least twice as fast as that!”

- Wrong environment to look for catchup and learning

Work on Learning

- Nathan and Camara (1998): 55% of the juniors taking the SAT in the US improved their scores as seniors while 35% of them experienced score reductions. The higher (lower) the student's initial SAT score as a junior, the lower (higher) is the increase in her score when retaking as a senior.
- Vigdor and Clotfelter (2003): use data on evolution of SAT scores over multiple attempts. Find more learning at bottom than top.
- SATs not best place to look for learning
  - Less important in admissions than ÖSS
  - Less difficult than ÖSS. Compromises ability to distinguish at the high end
  - Perfect (294 of 1.5m) or near to perfect scores (5683 of 1.5m) in the SATs.

What is the ÖSS?

- Every year, 1.5 million students take ÖSS in Turkey.
- Placement rate is about 30%
- 2/3 of the applicants are repeat takers
- Can look for learning as same exam
- If less privileged learn more on re-tries, potential for leveling playing field

Data Set

- Unique dataset on about 40,000 applicants each from three high school tracks (Science, Social Studies, Turkish/Math) in 2002 to estimate learning, in terms of *score improvement*, accounting for selection.
- Four data sources:
  - Application form: high school track, name and type of school, repeat taker
  - Survey applicant: household income, parents' education and occupation, family size, time and money spent on *dersanes*, number of previous attempts...
  - High school records: GPA at graduation
  - ÖSYM records: performance in the exam

Assumptions

- Key feature: data on GPA and ÖSS score
- Assumptions:
  - i) students know their own (unobserved to the econometrician) ability
  - ii) learning is draw from a distribution that varies with observables/unobservables
  - iii) performance is partly random
  - iv) system is in steady state..
- Develop dynamic model of retaking where costs of retaking vary over time

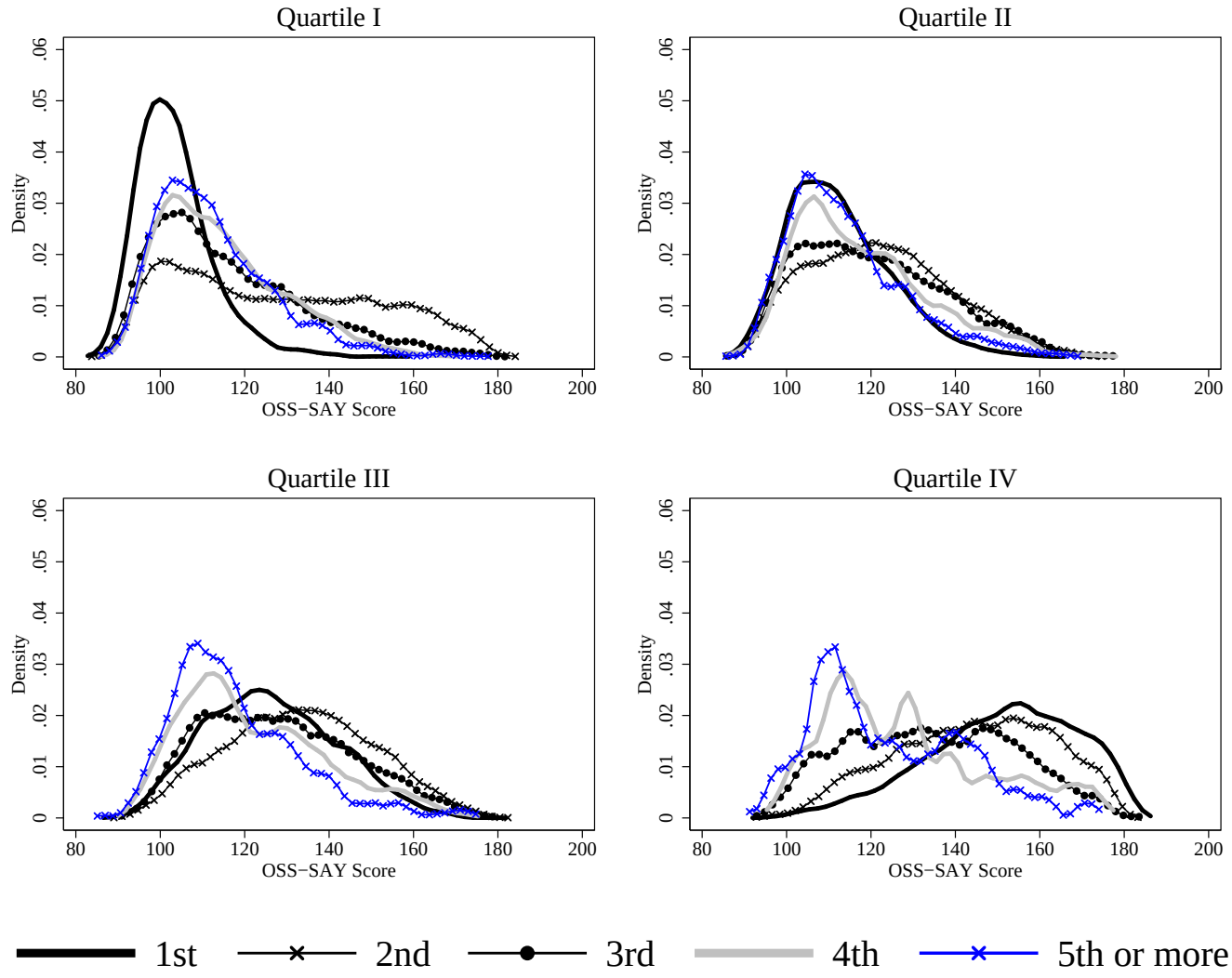
▸ Distribution of Scores by Track

Three Effects

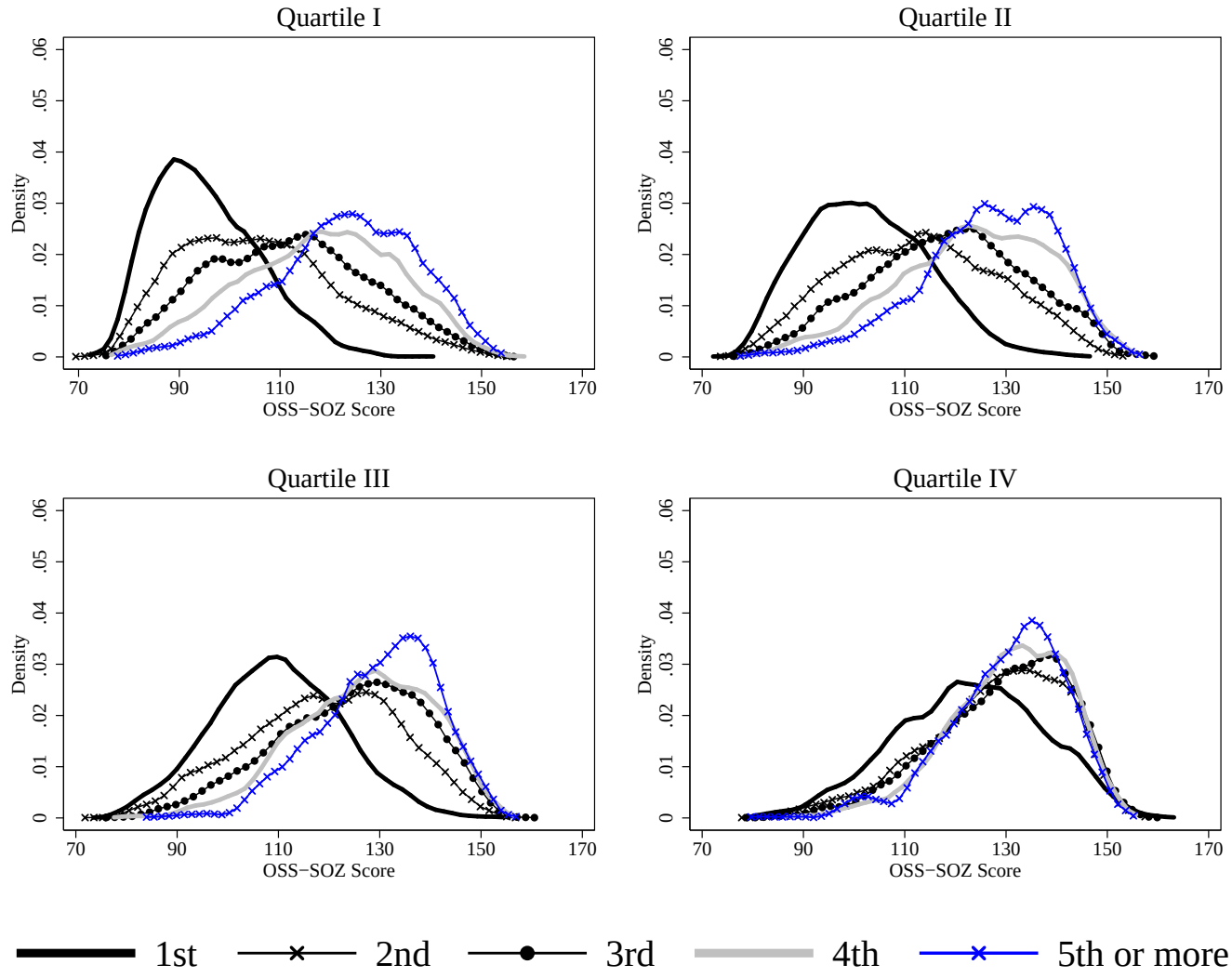
- Three Effects
  - Learning: Students who retake can *learn*. This raises scores and shifts the distribution of retakers to the right.
  - Selection: Students *choose* to retake/not. If worse students tend to retake, this effect will move the distribution of scores for retakers to the left
  - Composition: If above two occur differently across groups we could have a *composition* effect. For example, learning may be greater for the less privileged as they are further away from their "frontier"

▸ Composition Effect

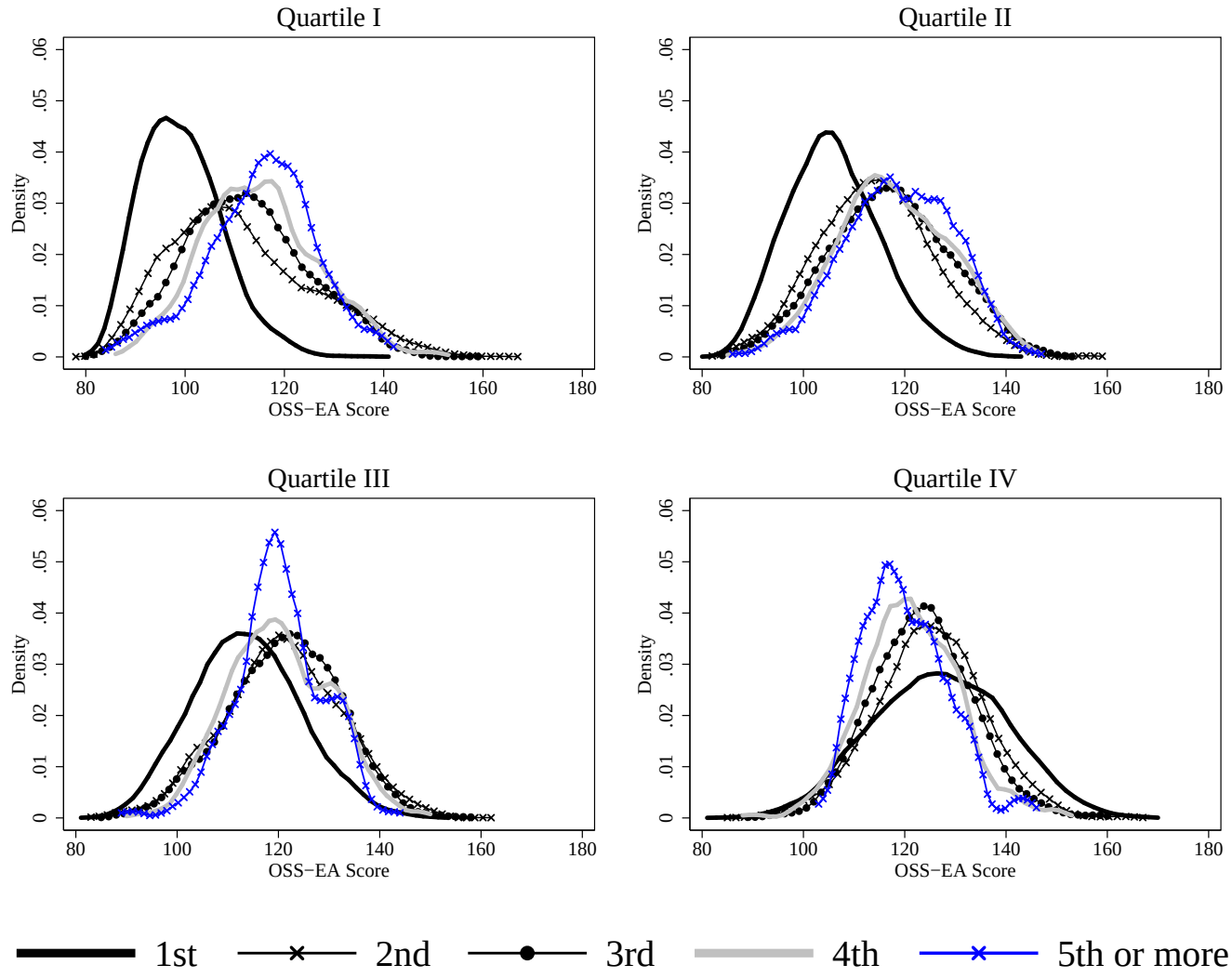
Distribution of Scores by GPA quartiles: Science



Distribution of Scores by GPA quartiles: Social Studies



Distribution of Scores by GPA quartiles: Turkish-Math



Learning Gains in ÖSS

- Challenging given lack of panel data.
- Repeat takers act as “Quasi Panel” given Steady State
- Measure cumulative learning between the first and the nth attempt.

Model

- High school GPA of i:

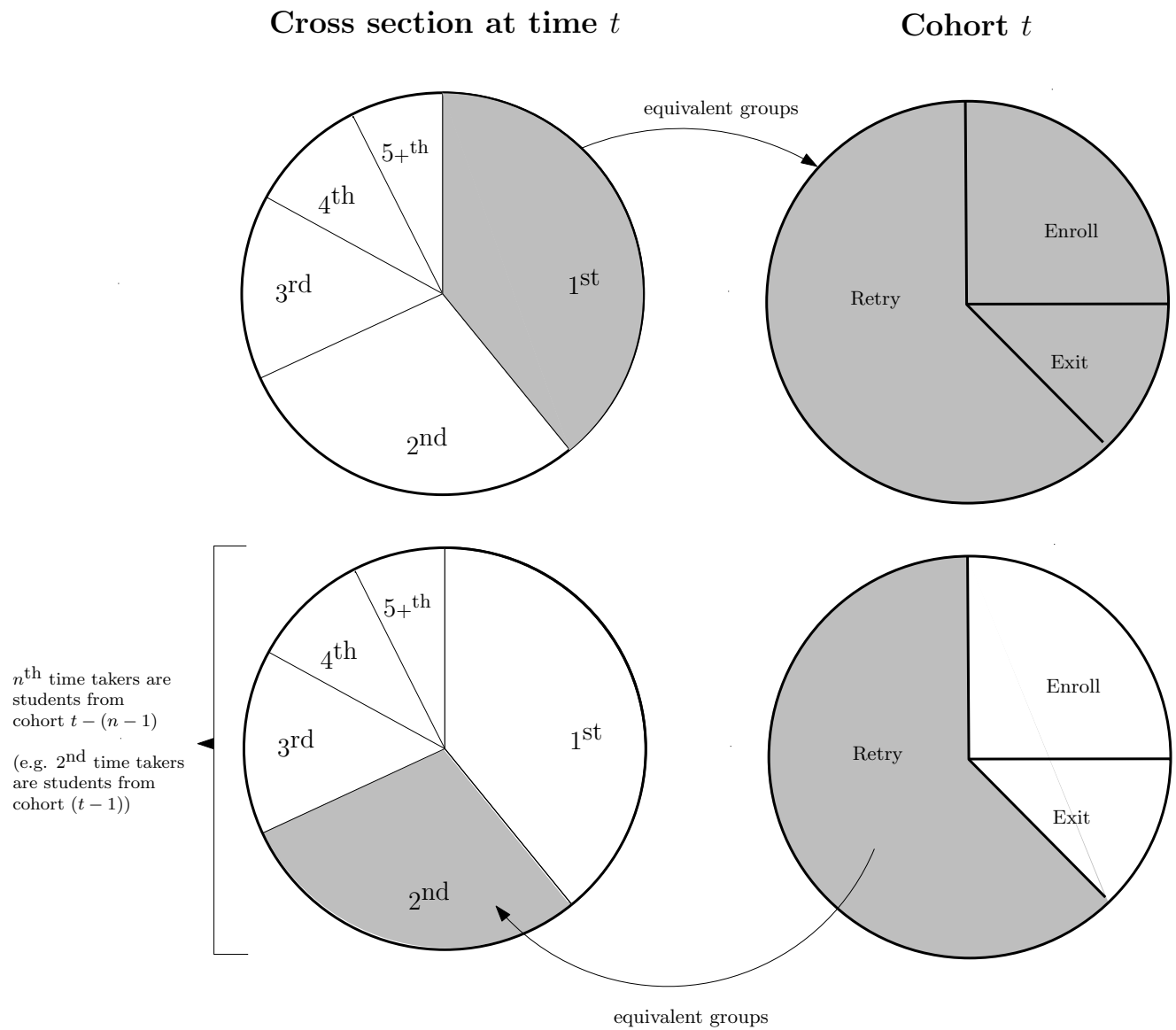
$$g_i = X_i\alpha_0 + \theta_i + \epsilon_{i0}$$

- Scores in the nth try:

$$s_{in} = X_i\alpha_1 + \sum_{k=2}^{n} \lambda_{ik} + \theta_i + \epsilon_{in}$$

λ_{ik}: marginal learning in kth try. Drawn from distributions that can depend on X, θ
X_i: observed characteristics
θ_i : unobserved ability
ϵ_{ik}, : exogenous shock
All $\epsilon_{ik}, \theta_i, X$ orthogonal to each other

Estimation Strategy: The Steady State Assumption



Estimation Strategy

1^{st} Time Takers

$$g_i = X_i\alpha_0 + \theta_i + \epsilon_{i0}$$
$$s_{i1} = X_i\alpha_1 + \theta_i + \epsilon_{i1}$$

$\Downarrow$

$\hat{\alpha}_0,\ \hat{\alpha}_1$

$\Rightarrow$

n^{th} Time Takers

$$g_i = X_i\alpha_0 + \theta_i + \epsilon_{i0}$$
$$s_{in} = X_i\alpha_1 + \sum_{k=2}^{n} \lambda_{ik} + \theta_i + \epsilon_{in}$$

$$g_i - X_i\hat{\alpha}_0 = \theta_i + \epsilon_{i0}$$
$$s_{in} - X_i\hat{\alpha}_1 = \sum_{k=2}^{n} \lambda_{ik} + \theta_i + \epsilon_{in}$$

$\Downarrow$

$$\begin{aligned} E(g_i - X_i\hat{\alpha}_0 | N_i = n) &= E(\theta_i | N_i = n) + E(\epsilon_{i0} | N_i = n) \\ &\approx E(\theta_i | N_i = n) \\ &= \hat{\theta}_n \end{aligned}$$

$\Downarrow$

$$\begin{aligned} E(s_{in} - X_i\hat{\alpha}_1 - \hat{\theta}_n | N_i = n) &= E\left(\sum_{k=2}^{n} \lambda_{ik} + \epsilon_{in} | N_i = n\right) \\ &= E\left(\sum_{k=2}^{n} \lambda_{ik} | N_i = n\right) \end{aligned}$$

Estimation Strategy: Interpretation

- Estimate the *cumulative* learning effect between the 1st and the n^{th} attempt: $\sum_{k=2}^{n} \lambda_{ik}$.
- Since λ_{ik} varies across individuals $\forall k$, mean learning for 2nd time takers may be different from mean learning for 3rd time takers in their second attempt.
- Therefore, difference between 3rd time takers' and 2nd time takers' cumulative learning should *not* be interpreted as marginal learning.

Results: Mean Cumulative Learning

Cumulative Learning in Points (100 scale)

	Attempts			
Track	2^{nd}	3^{rd}	4^{th}	$5^{th}+$
Science	9.7	6.8	6.6	6.2
	(0.09)	(0.11)	(0.13)	(0.14)
Social Studies	4.8	7.1	9.0	11.1
	(0.10)	(0.10)	(0.12)	(0.14)
Turkish-Math	6.7	7.1	7.9	9.5
	(0.06)	(0.09)	(0.15)	(0.23)

Note: Standard error of the mean in parenthesis.

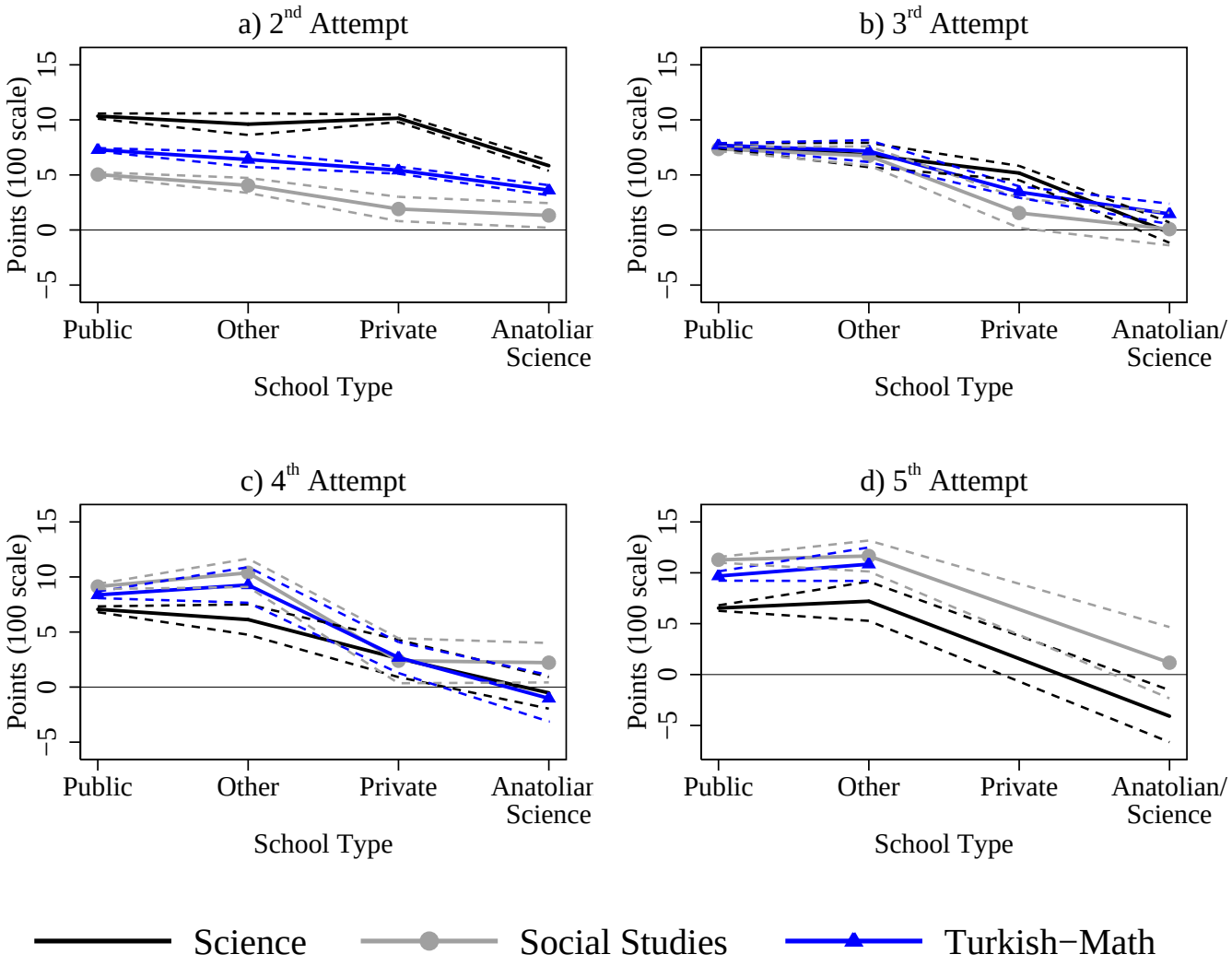
Results: Overall

- Learning more the less privileged in family background, school type, Coaching expenditure, . . .

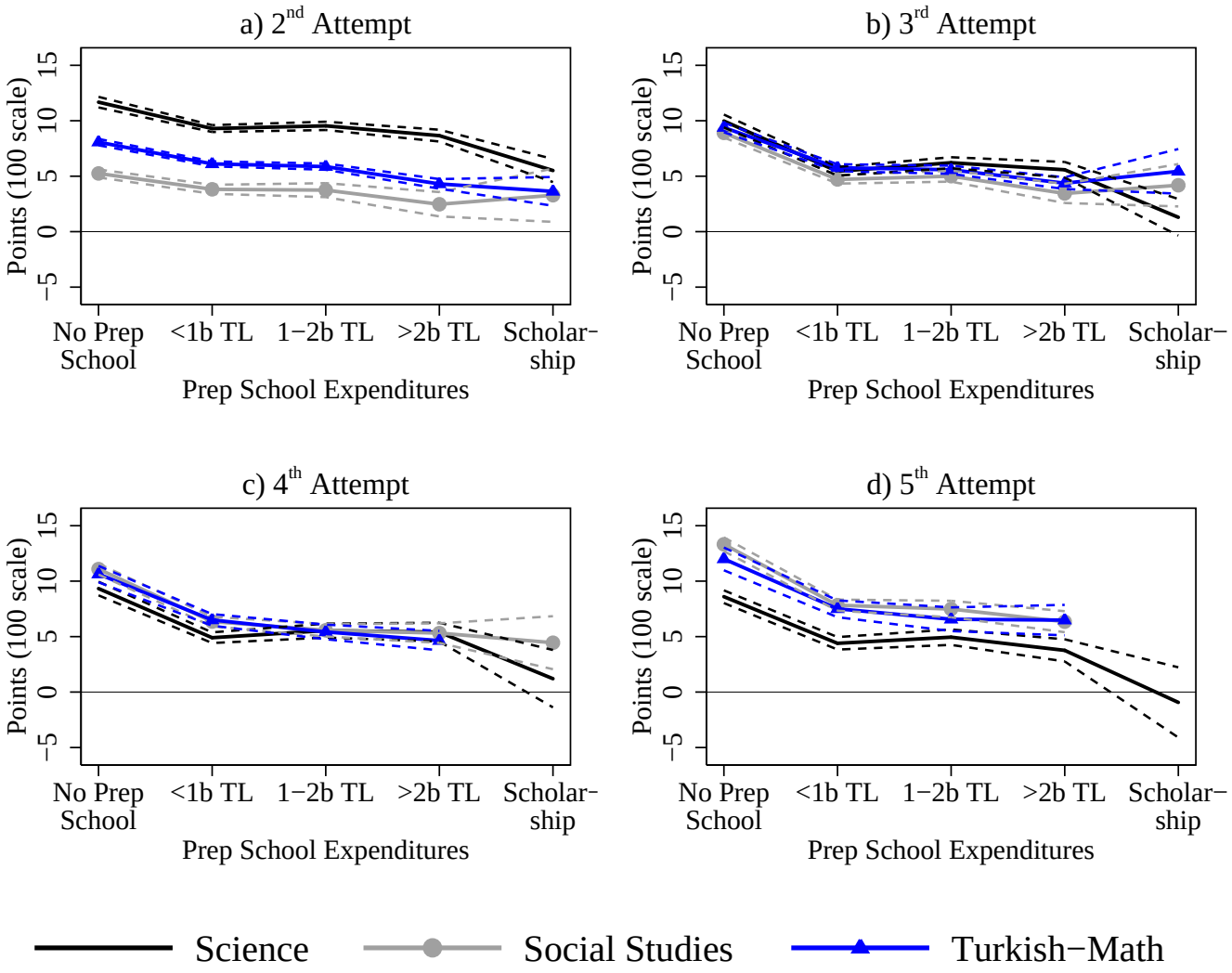
Results: Decomposition of Change in Mean Scores

	Attempts			
	2nd	3rd	4th	5th+
Science				
Mean Diff. between s_{in} and s_{i1}	*-0.9*	*-5.0*	*-7.1*	*-8.9*
Due to X_i	-3.6	-6.4	-8.0	-9.0
Due to θ	-6.9	-5.5	-5.7	-6.1
Due to $\sum_{k=2}^{n} \lambda_{ik}$	9.7	6.8	6.6	6.2
Social Studies				
Mean Diff. between s_{in} and s_{i1}	*3.7*	*6.7*	*8.7*	*9.9*
Due to X_i	-0.3	0.3	0.5	0.2
Due to θ	-0.8	-0.7	-0.8	-1.5
Due to $\sum_{k=2}^{n} \lambda_{ik}$	4.8	7.1	9.0	11.1
Turkish-Math				
Mean Diff. between s_{in} and s_{i1}	*1.7*	*2.1*	*2.1*	*2.2*
Due to X_i	-1.5	-2.0	-2.6	-3.1
Due to θ	-3.6	-3.0	-3.2	-4.1
Due to $\sum_{k=2}^{n} \lambda_{ik}$	6.7	7.1	7.9	9.5

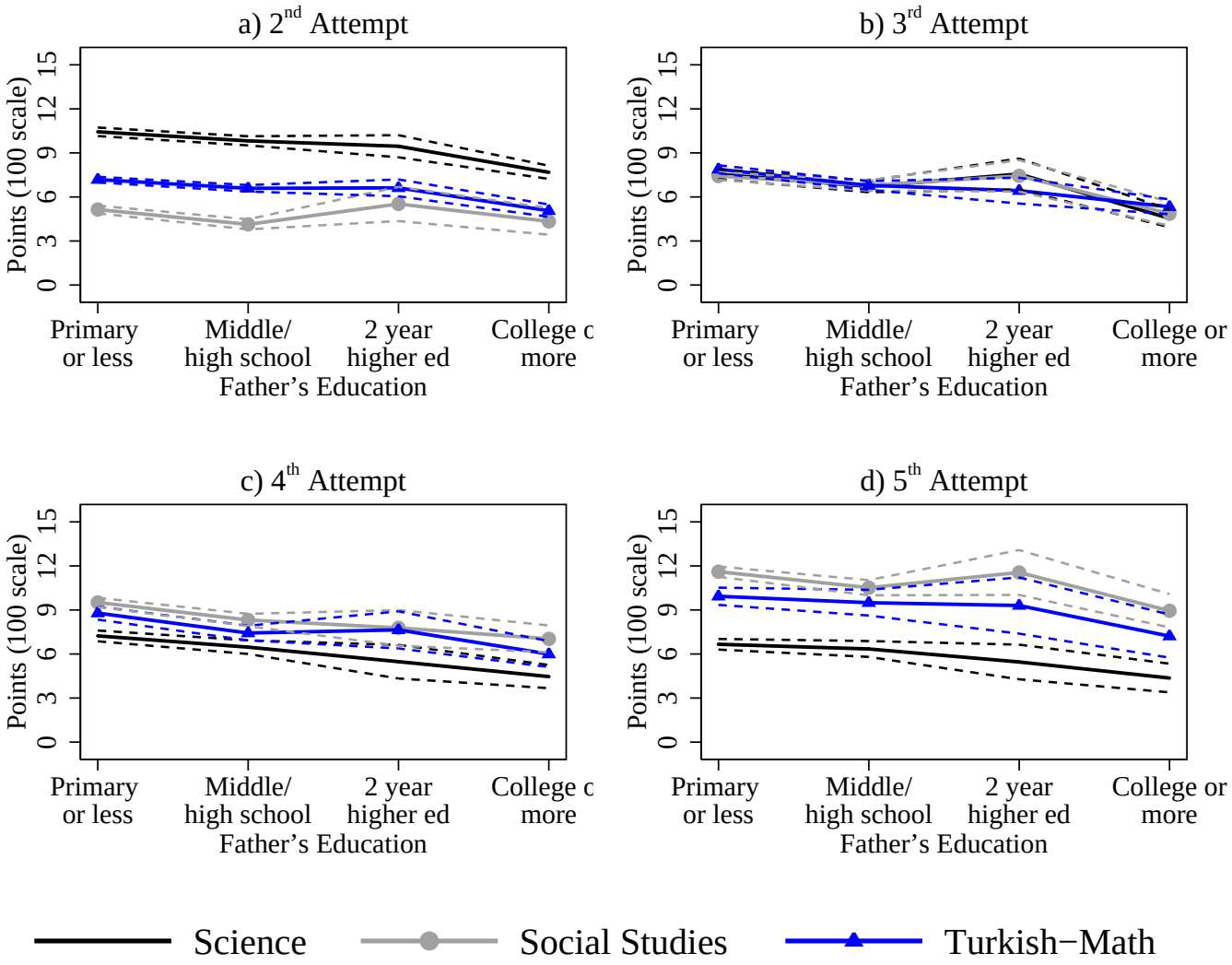
Results: Cum. Learning by School Type



Results: Cum. Learning by Coaching Expenditures



Results: Cum. Learning by Father's Education

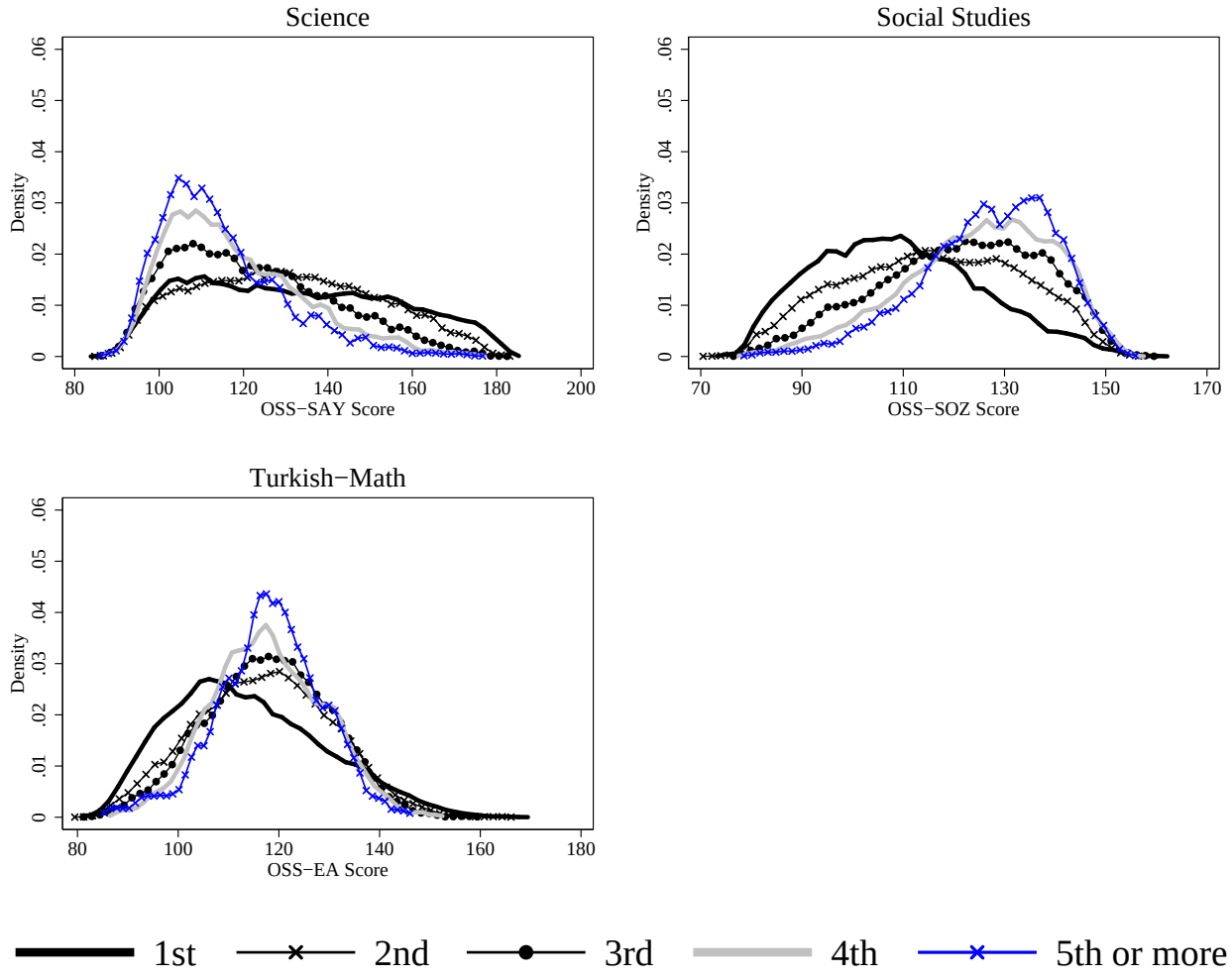


Conclusion and Future Agenda

- Less advantaged students exhibit larger performance improvements as they keep retaking.
  - Open competitive exams that can be taken more than once generate important learning gains for less advantaged students *before* they go to college.
- Though students in EEI fall back, this may be because of the moving goal post.
- Suggests two step approach
  - Identify talented
  - Provide pre-entry services

  may be more fruitful in leveling playing field

Distribution of Exam Scores



- First time takers perform worse (better) in Social Studies and Turkish-Math (Science). Go back

Composition

- Composition effect likely to be important
  - Across all subjects, less privileged learn more than more privileged
  - Science has more privileged, then Turkish Math, then Social Studies
  - Suggests least movement to right in retakers in Science and most in Social studies as seen

Go back