From Natural Variation To Optimal Policy? The Importance of Endogenous Peer Group Formation

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Presentation Valentin Stumpe

What's the Framework?

- **Definition Peer Group:** Social Group with similar interests and demographic background.
- *In a classroom:* The entirety of your classmates with whom you interact
- What effect do your peers abilities have on you, conditional on your own ability?
- Analyze effects, design reassignment algorithm to maximize academic peformance of low-ability students (design new classes!)
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1. Introduction to the Peer Literature
2. Empirical Strategy
3. Predicted Results
4. Actual Results
5. Discussion and Link to Roy-Model
6. Lookout

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Introduction to Peer Literature

- Peers play an important role on performance wherever they appear: *Workplace, Education, Day-to-Day Behavior*
- Large body of research dedicated to *identification* of peer effects, but only more recent papers tried to explore the potential of reassignment to maximize outcomes

A Selection of Evidence

- Sacerdote (2001) finds that peers (college roommates) have impact on GPA and decisions to join social groups (e.g. fraternities)
- Zimmerman (2003) uses data on grades, SAT scores, and SAT scores of roommates in quasi-experimental approach. Finds that verbal SAT scores seem to have the strongest peer effect
- Carrell, Fullerton and West (2009): Find persisting and nonlinear peer-effects in peer groups of $\sim$30 students
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- Peer effects may be a thing, but what should we make of the results?
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Carrell, Sacerdote, and West (2013)

Goals:

- Make use of pre-treatment data: Identify nonlinear peer effects at the United States Air Force Academy (USAFA) (2005 - 2010) to design optimal reassignment rules and test for its effectiveness (2011/2012)
- **Parameters of Interest**: Coefficient on High/Medium/Low-Ability Peers on student's performance, conditional on student's ability $\Rightarrow$ effect of being exposed to a designed peer group
- **Measure for Ability:** Consists of *SAT Verbal*, *SAT Math* and *Academic Composite*[1]-score
- **Outcome Measure: GPA**

[1] High school GPA, class rank and quality of high school attended

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Empirical Strategy

- Pre-Treatment: Students were randomly assigned to squadrons of $\sim$30 students $\Rightarrow$ *Find nonlinear peer effects*
- *Randomly* assign students to control or treatment group (20 squadrons each)
- Treatment: Use estimates from pre-treatment data to create squadrons designed to improve performance of students on the bottom tercile of the ability distribution.
- Subjects: Students in *low* tercile of ability distribution (called *low ability students*)

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Baseline Sample

TABLE I

SUMMARY STATISTICS[a]

Variables	(1) Pre-Treatment Group Mean (sd)	(2) Control Group Mean (sd)	(3) Treatment Group Mean (sd)
Grade Point Average	2.785	2.789	2.781
	(0.661)	(0.642)	(0.659)
Fraction of High SAT-V Peers	0.276	0.263	0.272
	(0.0742)	(0.0603)	(0.161)
Fraction of Low SAT-V Peers	0.236	0.242	0.244
	(0.0717)	(0.0584)	(0.0774)
SAT Verbal Score	6.342	6.327	6.323
	(0.682)	(0.661)	(0.667)
SAT Math Score	6.643	6.568	6.580
	(0.654)	(0.646)	(0.653)
Student is Female	0.180	0.208	0.216
	(0.384)	(0.406)	(0.412)
Observations	7160	1228	1219

Use the pre-treatment data

- A student's GPA (in squadron s of ability t) is determined by a variety of pre-treatment and demographic characteristics, denoted as a matrix X
- Other determinants are the leave-one-out average GPA of squadron s, $\overline{GPA}_{s-i}$ and, similarly, the leave-one-out mean of the pre-treatment characteristics-matrix X: $\overline{X}_{s-i}$
- Hence, one can estimate:

$$GPA_{st} = X\alpha_1 + \overline{GPA}_{s-i}\alpha_{2t} + \overline{X}_{s-i}\alpha_{3t} + \epsilon_{st}$$

- We can solve for the reduced form and take the limit (Number of peers $\rightarrow \infty$)

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Pre-Treatment Results

PEER EFFECTS IN THE PRE-TREATMENT GROUP[a]

Variables	(1) GPA	(2) GPA	(3) GPA	(4) GPA
Fraction of High SAT-V Peers	0.181[d]	0.190[c]		
	(0.094)	(0.096)		
Fraction of Low SAT-V Peers	−0.050	−0.061		
	(0.095)	(0.094)		
Fraction of High SAT-V Peers × High $\widehat{GPA}$			0.222	0.233
			(0.156)	(0.151)
Fraction of High SAT-V Peers × Middle $\widehat{GPA}$			−0.136	−0.119
			(0.136)	(0.137)
Fraction of High SAT-V Peers × Low $\widehat{GPA}$			0.464[b]	0.474[b]
			(0.150)	(0.152)
Fraction of Low SAT-V Peers × High $\widehat{GPA}$			0.026	0.009
			(0.144)	(0.147)
Fraction of Low SAT-V Peers × Middle $\widehat{GPA}$			−0.219	−0.230
			(0.145)	(0.142)
Fraction of Low SAT-V Peers × Low $\widehat{GPA}$			0.065	0.061
			(0.141)	(0.140)
Observations	14,024	14,024	14,024	14,024
R^2	0.345	0.345	0.346	0.345

What do we see?

- No significant estimated effect of the fraction of High-SAT peers on high (high predicted GPA) and middle ability students, but significant, positive effect on low ability students
- Conversely, no negative estimated effect of low ability students on high ability students
- So, *randomly* assign half of the incoming classes to control and treatment group, respectively
- Then use algorithm to efficiently maximize the fraction of high ability peers for each low ability student in treatment group *s.t.* bureaucratic constraints

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Reassignment

- Note: Students were *randomly* assigned to control and treatment group, respectively, so no selection bias on *this* treatment level
- Students in control group were **randomly assigned** to one of the 20 control squadrons subject to diversity constraints in the squadrons
- Students in treatment group were **sorted** into one of the 20 treatment squadrons according to reassignment-algorithm

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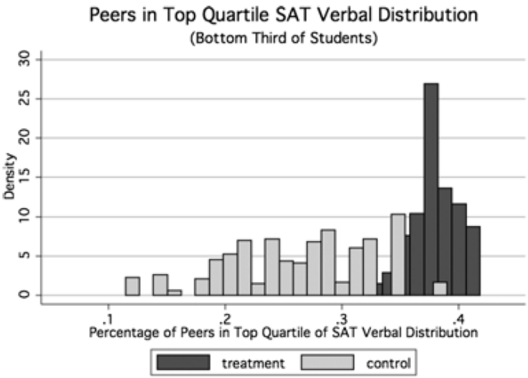
Reassignment

- Algorithm creates two types of squadrons: Groups low ability students with high ability students (bimodal) and medium ability students with other medium ability students (homogeneous)
- Leave-one-out mean SAT verbal score for low-ability-students raises from .28 to .38: Peers are "better"



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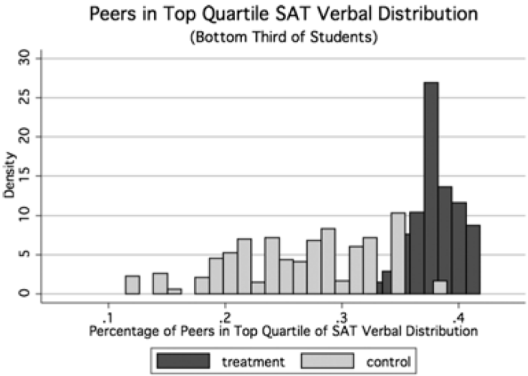

Outline

Predicted treatment effect using the pre-treatment estimates:

TABLE IV

PREDICTED TREATMENT EFFECT[a]

Variables	(1) All Students	(2) Bottom $\widehat{GPA}$	(3) Middle $\widehat{GPA}$	(4) Top $\widehat{GPA}$
Student in Treatment Group	2.787	2.390	2.783	3.198
	(0.026)	(0.027)	(0.027)	(0.027)
Student in Control Group	2.772	2.336	2.767	3.195
	(0.026)	(0.027)	(0.027)	(0.026)
Predicted Treatment Effect	0.015	0.053[b]	0.016	0.003
	(0.037)	(0.037)	(0.037)	(0.037)
Observations	2653	881	884	888

Outline

Observed treatment effect:

TABLE VI
OBSERVED TREATMENT EFFECTS[a]

Variables	(1) All Students	(2) Low $\widehat{GPA}$	(3) Middle $\widehat{GPA}$	(4) High $\widehat{GPA}$
Student in Treatment Group	0.001	−0.061[c]	0.082[b]	−0.012
	(0.022)	(0.031)	(0.039)	(0.036)
Observations	4834	1571	1626	1637
R^2	0.357	0.136	0.067	0.151

Actual Results

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Possible Explanations

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- Peer dynamics and endogenous peer group formation

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- Design implicitly assumed peer dynamics to remain comparable to pre-treatment dynamics
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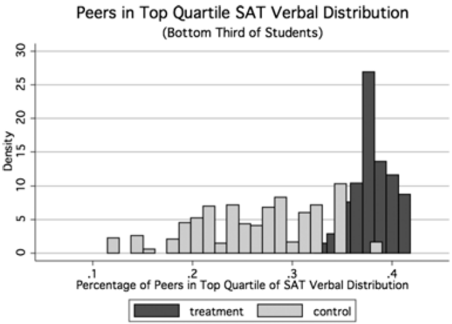
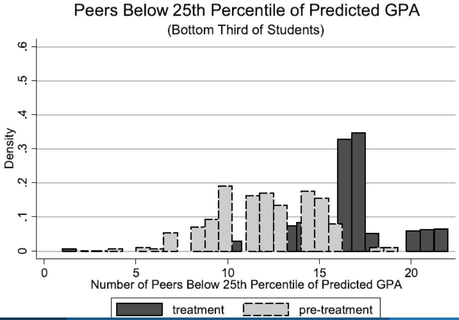

Peers in Top Quartile SAT Verbal Distribution
(Bottom Third of Students)
Density
0
5
10
15
20
25
30
.1
.2
.3
.4
Percentage of Peers in Top Quartile of SAT Verbal Distribution
treatment
control


Peers Below 25th Percentile of Predicted GPA
(Bottom Third of Students)
Density
0
.1
.2
.3
.4
.5
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Number of Peers Below 25th Percentile of Predicted GPA
treatment
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Possible Explanations

- Low ability students in treatment group were assigned a large number of high ability peers, but also large number of low ability peers.
- *True* peer group of a student may not be the whole squadron, but a smaller and endogenously chosen subgroup of similar peers
- So being assigned to treatment changed availability of similar peers and increased the attractiveness of forming a subgroup with similar students *(homophily)*
- Could this drive the surprising results?

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Peer Dynamics as an Explanation

- Examine this explanation using survey and housing data on the subjects
- Confirms this suspicion: low ability students in the treatment squadrons $\sim$17 percentage points more likely to have low predicted GPA study partners than low ability students in the control squadron
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- Assignment to treatment may be random, *intended* treatment is not! $\Rightarrow$ *Behavioral response to assignment to treatment*

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- Let $D*$ denote random assignment to the intended treatment (*Gold Standard*), $R = 1$ if a student for whom $D* = 1$ is randomized into the treatment group (*Not actual treatment*) and A denote *actual* treatment.
- The important assumption needed to use of the CSWs randomization is that it actually translates into randomization on the intended treatment level: $E[Y_1* - Y_0*|D* = 1] = E[Y_1 - Y_0|A = 1]$. However (with abuse of notation):

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What can we make of the results?

- Was there a way to predict this would happen? Could it have been avoided/ accounted for?
- Yes! Survey data reveals interactions not accounted for when designing "optimal" peer groups designed by algorithm
- Can we proxy for these interactions? Are there determinants of peer interaction?

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Where To Go From Here

- What Lukas Kießling and I are currently working on
- Find drivers of homophily using self-reported scores on non-ability characteristics: *prosociality, problem behavior, OCEAN etc*
- Use estimates of correlation structure from real data (using NEPS) to parameterize simulation of different reassignment rules
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	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
High ability × Leave-one-out mean math skill (std.)	0.26***	-0.22**	-0.20**	-0.20**	-0.23**	-0.21**	-0.21**	-0.21**	-0.29***
	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)
Medium ability × Leave-one-out mean math skill (std.)	-0.54***	-0.19**	-0.17*	-0.17*	-0.20**	-0.18**	-0.19**	-0.19**	-0.27***
	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.10)	(0.10)
Low ability × Leave-one-out mean math skill (std.)	-0.79***	0.23*	0.23*	0.24*	0.22	0.25*	0.24*	0.23*	0.16
	(0.13)	(0.14)	(0.14)	(0.14)	(0.14)	(0.14)	(0.14)	(0.14)	(0.14)
Gender	0.07	0.18***	0.19***	0.19***	0.20***	0.12***	0.12***	0.13***	0.12***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Age in Months	-0.02***	-0.01***	-0.01***	-0.01***	-0.01***	-0.01***	-0.01***	-0.01***	-0.01***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Migration Background	-0.08	-0.02	-0.01	-0.01	-0.01	-0.03	-0.03	-0.03	-0.02
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
Class Size in Wave 1	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Mathematics skill (std.)		0.65***	0.65***	0.65***	0.65***	0.62***	0.62***	0.62***	0.61***
		(0.04)	(0.04)	(0.04)	(0.04)	(0.03)	(0.03)	(0.04)	(0.04)
Openness Std.			-0.03	-0.03*	-0.03*	-0.03*	-0.03	-0.03	-0.03
			(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Mean Openness				-0.08	-0.06	-0.07	-0.07	-0.08	-0.05
				(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.10)
Neuroticism Std.					-0.03*	-0.04**	-0.05**	-0.05**	-0.05**
					(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Mean Neuroticism					-0.11	-0.08	-0.09	-0.09	-0.02
					(0.08)	(0.08)	(0.08)	(0.08)	(0.09)
Conscientiousness Std.						0.18***	0.18***	0.18***	0.19***
						(0.02)	(0.02)	(0.02)	(0.02)
Mean Conscientiousness						-0.14*	-0.15*	-0.14*	-0.09
						(0.08)	(0.08)	(0.08)	(0.08)
Extraversion Std.							-0.04**	-0.04**	-0.04*
							(0.02)	(0.02)	(0.02)
Mean Extraversion							-0.03	-0.04	0.01
							(0.08)	(0.08)	(0.08)
Agreeableness Std.								-0.02	-0.02
								(0.02)	(0.02)
Mean Agreeableness								-0.02	-0.03
								(0.10)	(0.10)
Average Gender									-0.37**
									(0.19)
School FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	2914	2914	2883	2883	2866	2857	2839	2826	2826
R^2	.21	.31	.31	.31	.31	.34	.34	.34	.34

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
High ability × Leave-one-out mean math skill (std.)	0.05	-0.03	-0.02	-0.02	-0.04	-0.04	-0.03	-0.04	-0.07
	(0.09)	(0.07)	(0.08)	(0.08)	(0.08)	(0.07)	(0.07)	(0.08)	(0.08)
Medium ability × Leave-one-out mean math skill (std.)	-0.19**	-0.25***	-0.23***	-0.23***	-0.26***	-0.23***	-0.22***	-0.23***	-0.26***
	(0.08)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)
Low ability × Leave-one-out mean math skill (std.)	-0.31***	-0.20***	-0.19**	-0.18**	-0.21***	-0.17**	-0.16**	-0.17**	-0.19***
	(0.08)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)
Gender	-0.05	0.17***	0.18***	0.18***	0.19***	0.10***	0.10***	0.10***	0.10***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Age in Months	-0.02***	-0.02***	-0.01***	-0.01***	-0.01***	-0.01***	-0.01***	-0.01***	-0.01***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Migration Background	-0.10**	0.00	0.01	0.01	0.01	0.01	0.01	0.01	0.01
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Class Size in Wave 1	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Mathematics skill (std.)		0.55***	0.55***	0.55***	0.54***	0.54***	0.53***	0.53***	0.53***
		(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Openness Std.			-0.02*	-0.02	-0.02	-0.03**	-0.03*	-0.02*	-0.02*
			(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Mean Openness				0.06	0.07	0.06	0.05	0.05	0.06
				(0.06)	(0.06)	(0.07)	(0.07)	(0.07)	(0.07)
Neuroticism Std.					-0.03*	-0.03**	-0.04***	-0.04***	-0.04***
					(0.01)	(0.01)	(0.02)	(0.02)	(0.02)
Mean Neuroticism					-0.12*	-0.11	-0.12*	-0.12*	-0.10
					(0.07)	(0.07)	(0.07)	(0.07)	(0.08)
Conscientiousness Std.						0.19***	0.19***	0.20***	0.20***
						(0.01)	(0.01)	(0.01)	(0.01)
Mean Conscientiousness						-0.06	-0.06	-0.05	-0.04
						(0.06)	(0.06)	(0.07)	(0.07)
Extraversion Std.							-0.04**	-0.04**	-0.04**
							(0.01)	(0.01)	(0.01)
Mean Extraversion							-0.02	-0.03	-0.02
							(0.07)	(0.07)	(0.07)
Agreeableness Std.								-0.01	-0.01
								(0.01)	(0.01)
Mean Agreeableness								-0.02	-0.02
								(0.07)	(0.07)
Average Gender									-0.15
									(0.15)
School FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	4777	4777	4719	4719	4693	4672	4646	4612	4612
R^2	.15	.28	.28	.29	.29	.32	.32	.32	.32

- Not a big effect, but interesting to explore correlation structure of "soft-skills" with ability interactions
- Maybe we can start from here or even approach the peer literature from a Roy-Model point-of-view $\Rightarrow$ literature scarce!

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- Questions?

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