Abstract Title Page
Not included in page count.

Title:

Inference on Peer Effects with Missing Peer Data: Evidence from Project STAR

Author(s):

Aaron Sojourner, University of Minnesota

Abstract Body

Limit 5 pages single spaced.

Background/context:

Description of prior research and/or its intellectual context and/or its policy context.

Imagine yourself in the position of an elementary-school principal about to start a new school year. You can access records that describe each student's background characteristics and past years' test scores. You must decide how to divide the students into classes. If each student's classmates affect her outcomes, then your class-composition decision has consequences for the students and for society. Answers to some empirical questions would help with your decision.

How can students' outcomes be expected to differ depending on their peers? What tradeoffs do you face in choosing one class-composition policy versus another? Understanding how peer effects work would be useful.

A large literature on peer effects in education aims to generate insight into how classroom peers affect student outcomes. Peer effects also play a prominent role in research on workplace teams, health habits, marketing, neighborhood influences, price bubbles, crime, microfinance and peer-lending circles, and elsewhere.

Peer-effects researchers confront at least two methodological challenges. First, one must separate the causal effects of peers from “correlated effects," the influence exerted by omitted variables that are correlated with peer measures (Manski (1993)). Researchers analyzing normal administrative data sets from school districts do not generally understand the process of student and teacher sorting well enough to model selection credibly. Consequently, estimates can suffer from omitted-variable bias, mistaking the influence of unobserved factors for the causal influence of peers. Though difficult to address, this challenge is well understood and receives a great deal of attention in most empirical papers.

Second, researchers must deal with the challenge posed by any missing data on variables theorized to influence peers. Methods and intuitions for dealing with missing data that were developed in other contexts do not translate immediately to peer-effects research. Peer effects research differs because missing information about one individual does not remain isolated to that individual's observation. Rather, it spills over as missing peer information for all of the individual's peers as well.

The challenge posed by missing data on peer-influencing covariates rarely receives attention in the literature though this kind of missing data pervades empirical peer-effects research. Many studies deal with missing data using an estimation procedure this paper terms an individual-deletion procedure (IDP): delete individuals with missing covariate data and carry out the analysis as if the remaining individuals represented the population. Consider these examples from recent studies of peer effects in education. In K-12 schools, Vigdor and Nechyba (2007) drop about 20 percent of students in this way. Lefgren (2004) drops between 8 and 10 percent of various cohorts. Atkinson, Burgess, Gregg, Propper, and Proud (2008), Burke and Sass (2008), and Zabel (2008) do the same without specifying the percentage of individuals dropped. Foster

(2006) studies peer effects at the University of Maryland. She drops at least 10 percent of individuals due to missing data. Arcidiacono and Nicholson (2005) drop about 35 percent from their study of peer effects in medical schools.

Though convenient, the properties of IDP estimates are not well understood. IDP are often employed without much comment or theoretical justification. The only previous work in this area, Ammermueller and Pischke (2006), assumes that the missing and observed data share a common distribution and is, therefore, inapplicable when there is selection into missingness or data missing not at random. The current paper shows that IDP estimators are generally biased and inconsistent and relates this bias to the interplay between the data-missingness and the group-formation processes.

Purpose/objective/research question/focus of study:
Description of what the research focused on and why.

This paper contributes empirically to the literature on peer effects in first-grade classrooms. The paper examines peer effects on academic achievement among first graders randomly assigned to their classrooms and to their teachers as part of Tennessee's Project STAR, America's largest-ever education experiment. The analysis draws on previously unexploited measures of kindergarten achievement taken before random assignment to first-grade classes and available for about sixty percent of this sample. Data are not missing at random. This paper studies effects of peer lagged achievement on first-grade achievement.

The STAR data allow for credible inference about peer effects because students and teachers were randomly assigned to classes within school. Further, the data contain pre-assignment measures of achievement, which are useful as conditioning variables to explain each student's own outcome and for characterizing each student's peer group.

The paper contributes methodologically to the larger peer-effects literature in advancing our understanding of how to make inference about peer effects in the presence of missing data on peers.

Setting:
Specific description of where the research took place.

The original STAR study was carried out in 76 elementary schools in Tennessee in the mid-1980s.

Population/Participants/Subjects:
Description of participants in the study: who (or what) how many, key features (or characteristics).

The paper studies classroom peer effects among the 4,794 Project-STAR first graders in 210 nonsmall classes. Word (1990) and Krueger (1999) provide detailed discussions of the design and implementation.

Intervention/Program/Practice:
Specific description of the intervention, including what it was, how it was administered, and its duration.

To identify peer effects, the paper exploits the random assignment of students and teachers to classes within school. This generates random variation in students' peer groups and allows unbiased inference about peer effects.

Research Design:
Description of research design (e.g., qualitative case study, quasi-experimental design, secondary analysis, analytic essay, randomized field trial).

This paper analyzes the publicly-available Project STAR data in a new way. In design, it is effectively a randomized field trial exploiting within-school variation in peer "treatments." Random assignment of students and teachers to classes guards against omitted-variable bias. Each student is randomly-assigned a peer group. Proper handling of the missing data avoids bias that would otherwise arise due to measurement error.

Data Collection and Analysis:
Description of plan for collecting and analyzing data, including description of data.

The data are publicly available. Available information includes each student's school and classroom attended, background characteristics (gender, birthday, race, low-income status), end-of-first-grade achievement levels, and teacher characteristics. Kindergarten achievement is available for about 60% of students, those who attended kindergarten in the previous year at a STAR school. For the 40% of students who did not, no kindergarten achievement data is available. Table 1 describes measures and Table 2 provides sample summary statistics.

A major methodological contribution of this paper is developing a way to obtain unbiased estimates of peer effects in the presence of missing data on peers while allowing for data to be missing not at random. The approach relies on the random assignment of missing data students within schools and uses a decomposition of the true peer variables into observed and unobserved portions.

Findings/Results:
Description of main findings with specific details.

The effect of mean peer lagged achievement for all students is estimated. Estimates assuming homogeneous effects suggest that, on average, end-of-first-grade achievement rises moderately as mean peer lagged achievement rises (Table 5). The paper then permits heterogeneous peer effects, allowing the strength of peer effects to differ between students with low, middle, and high levels of lagged achievement. The evidence weakly suggests that lower-achieving students benefit more than higher-achieving students do from increases in the peer mean (Table 7). Similarly, there is evidence that raising the fraction of peers who are low-achieving hurts all students' outcomes but may hurt low achievers the most (Table 8).

Conclusions:
Description of conclusions and recommendations of author(s) based on findings and over study. (To support the theme of 2009 conference, authors are asked to describe how their conclusions and recommendations might inform

one or more of the above noted decisions—curriculum, teaching and teaching quality, school organization, and education policy.)

This paper contributes to our understanding of the tradeoffs involved in different student grouping policies in early elementary school. The estimates suggest that compared to a policy of achievement tracking, a policy of achievement mixing would raise average student achievement and reduce the differences in average outcomes between low, middle and high kindergarten achievers.

Appendixes

Not included in page count.

Appendix A. References

References are to be in APA format. (See APA style examples at the end of the document.)

Ammermueller, A. and J.-S. Pischke (2006). Peer Effects in European Primary Schools: Evidence from PIRLS. *IZA Discussion Paper*. No. 2077.

Arcidiacono, P. and S. Nicholson (2005). Peer effects in medical school. *Journal of Public Economics*, 89(2-3), 327-350.

Atkinson, A., S. Burgess, P. Gregg, C. Propper, and S. Proud (2008). The Impact of Classroom Peer Groups on Pupil GCSE Results. *Working paper.*

Burke, M. A., and T. R. Sass (2008). Classroom Peer Effects and Student Achievement. *Working paper.*

Foster, G. (2006). It's not your peers, and it's not your friends: Some progress toward understanding the educational peer effect mechanism. *Journal of Public Economics*, 90(8-9), 1455-1475.

Krueger, A. B. (1999). Experimental Estimates of Education Production Functions. *Quarterly Journal of Economics*, 114(2).

Lefgren, L. (2004). Educational peer effects and the Chicago public schools. *Journal of Urban Economics*, 56.

Manski, C. F. (1993). Identification of Endogenous Social Effects: The Reflection Problem. *The Review of Economic Studies*, 60(3).

Vigdor, J., and T. Nechyba (2007). Peer Effects in North Carolina Public Schools. In Woessmann and Peterson (Eds.), *Schools and the Equal Opportunity Problem.* Cambridge: MIT.

Word, E. et al (1990). The State of Tennessee's Student/Teacher Achievement Ratio (STAR) Project: Technical Report 1985-1990. *Discussion paper, Tennessee State Department of Education.*

Zabel, J. E. (2008). The Impact of Peer Effects on Student Outcomes in New York City Public Schools. *Education Finance and Policy*, 3(2).

Appendix B. Tables and Figures

Not included in page count.

Table 1: Variables and measures

y	Average of student's observed, nationally-normed Stanford Achievement Test math, reading and listening percentiles at the end of first grade (G1)
x	*Own covariates*
	Own-demographic variables
x_1	Same as y except from end of kindergarten (GK)
	Number of days absent in GK
	Indicators that student is African-American, is female, and qualifies for free- or reduced-price lunch in G1.
	Both student's years of age on Sept. 30, 1986 and an indicator student was age-eligible for first-grade prior to the study year.
	Class variables
	Total number of students in each student's first-grade class
	Indicator student in regular type class. Regular-with-aide type omitted.
	Teacher's years of teaching experience
	Indicators that teacher has a masters or higher degree and that teacher is on a Tennessee career ladder step.
	Peer-demographic variables
	Three variables measuring the fraction of each student's G1 classmates who are African-American, who are female, and who are low-income.
	Other variables
v	Variable by which student influences peers $\equiv g(x)$. Either x_1 or $(1(x_1 \leq 33.3), 1(x_1 \geq 66.7))'$.
z	Indicator that student's own v is observed
p	Fraction of student's G1 classmates with $z = 1$
1_s	Vector of school indicators

Table 2: Summary statistics for students in first-grade, non-small classes

Variable	Mean	Std. Dev.	N or % observed	R^2	
				1_s	1_c
Individual variables					
G1 achievement percentile, y	50.7	24.7	96.9	0.28	0.33
GK achievement percentile, x_1	54.5	20.7	57.7	0.27	0.31
Indicator x_1 in bottom tercile	0.17		57.7	0.19	0.23
Indicator x_1 in top tercile	0.31		57.7	0.16	0.21
GK number of days absent	10.1	9.3	60.6	0.10	0.13
1(x_1 observed), z	0.58		4794	0.07	0.09
African-American indicator	0.33		99.4	0.70	0.71
Female indicator	0.48		99.7	0.01	0.02
Low-income indicator	0.52		97.1	0.29	0.31
Years of age	6.7	0.5	100	0.04	0.07
Old-for-grade indicator	0.21		100	0.04	0.08
First-grade classroom peer variables					
Share of peers with x_1 observed, p	0.58	0.16	100	0.72	0.98
Mean x_1 among observed peers, $\bar{x}_1^{ob}$	54.4	11.9	100	0.87	0.99
Class-level variables					
Class size	23.1	2.4	100	0.82	1.00
Regular class indicator	0.53		100	0.08	1.00
Teacher has masters indictor	0.34		100	0.42	1.00
Teacher's years of exper.	11.4	9.0	100	0.39	1.00
Teacher on career ladder indicator	0.71		100	0.46	1.00

R^2 from regression of the variable on school dummies 1_s or class dummies 1_c

Table 5: Effect of peer mean using p-weight estimator among all students

Dependent variable: own first-grade achievement y				
Independent Variables	A	B	C	D
Observed peer mean achievement × fraction of peers observed $\bar{x}_1^{ob} \cdot p$	0.27 (0.20)	0.27 (0.20)	0.32 (0.20)	0.26 (0.20)
Own GK achievement $x_1 \times z$	0.85*** (0.02)	0.80*** (0.02)	0.80*** (0.02)	0.80*** (0.02)
Days absent in GK $\times z$		-.07* (0.04)	-.07* (0.04)	-.07* (0.04)
African-American indicator		-9.50*** (2.12)	-9.50*** (2.10)	-10.21*** (2.19)
African-American indicator $\times z$		5.35** (2.64)	5.36** (2.59)	5.56** (2.60)
p· school	Y	Y	Y	Y
School fixed effects $\times z$	Y	Y	Y	Y
Other own-demographic $\times z$	Y	Y	Y	Y
Class variables $\times z$	N	N	Y	Y
Peer demographic variables	N	N	N	Y
Number of schools	75	75	75	75
Number of classes	210	210	210	210
Number of students	4410	4410	4410	4410
Adjusted R^2	0.53	0.56	0.56	0.56

Coefficient (within-class-corrected SE). Significance: *: 10% **: 5% ***: 1%

Other own demographic, class and peer variables listed in Table 1.

Table 7: Heterogeneous effects of peer mean among those with own-kindergarten achievement observed

Dependent variable: own first-grade achievement y				
Independent Variables	A	B	C	D
p-weight estimator				
Effect of observed peer mean GK achievement × fraction of peers observed $\bar{x}_1^{ob}p$ for				
Own-x_1 in bottom tercile	-0.02	0.04	0.23	0.35
	(0.25)	(0.24)	(0.26)	(0.28)
Own-x_1 in middle tercile	0.04	0.09	0.19	0.32
	(0.24)	(0.23)	(0.25)	(0.27)
Own-x_1 in top tercile	-0.11	-0.03	0.11	0.24
	(0.24)	(0.24)	(0.25)	(0.28)
p- school	Y	Y	Y	Y
IDP estimator				
Effect of observed peer mean GK achievement $\bar{x}_1^{ob}$ for				
Own-x_1 in bottom tercile	0.31**	0.36***	0.42***	0.42***
	(0.16)	(0.14)	(0.14)	(0.14)
Own-x_1 in middle tercile	0.23**	0.25**	0.27**	0.27**
	(0.11)	(0.11)	(0.11)	(0.11)
Own-x_1 in top tercile	-0.10	-0.09	-0.02	0.03
	(0.13)	(0.14)	(0.13)	(0.13)
p- school	N	N	N	N
Both				
Tercile × school fixed effects	Y	Y	Y	Y
Tercile ×$(1, x_1)$	Y	Y	Y	Y
Tercile × other own variables	N	Y	Y	Y
Tercile × class variables	N	N	Y	Y
Tercile × peer demographic variables	N	N	N	Y
Number of schools	75	75	75	75
Number of classes	210	210	210	210
Number of students	2684	2684	2684	2684

Coefficient (within-class-corrected SE). Significance: *: 10% **: 5% ***: 1%
Full interaction of covariates with own-tercile. For terciles 2 and 3, estimates are main peer effect plus effect of peer-by-own-tercile indicator.

Table 8: Effect of fraction of peers in each achievement tercile by own achievement tercile among those with own-kindergarten achievement observed $z = 1$

Dependent variable: own first-grade achievement y			
Independent variables:	Fraction of observed peers' x_1 in:		
	Bottom tercile$\times p$	Middle tercile omitted	Top tercile$\times p$
Own-x_1 in bottom tercile	-25.65		-2.77
	(16.88)		(14.87)
Own-x_1 in middle tercile	-17.35		0.26
	(13.86)		(10.55)
Own-x_1 in top tercile	-12.58		-5.59
	(16.74)		(10.43)
$p\cdot$ school		Yes	
Tercile $\times$ school fixed effects		Yes	
Tercile $\times(1, x_1)$		Yes	
Tercile $\times$ other own variables		Yes	
Tercile $\times$ class variables		Yes	
Tercile $\times$ peer demographics		Yes	
Number of schools		75	
Number of classes		210	
Number of students		2684	

Coefficient (within-class-corrected SE). Significance: *: 10% **: 5% ***: 1%

Full interaction of covariates with own-tercile. For own tercile 2 and 3, estimates of fraction-of-peers effects are main effects plus own tercile by fraction-of-peers interaction term.

APA Reference Style Examples

Sample Citation: Journal Article

Hypericum Depression Trial Study Group. (2002). Effect of Hypericum perforatum (St John's Wort) in major depressive disorder: A randomized controlled trial. *JAMA, 287,* 1807–1814.

Sample Citation: Newsletter/Newspaper Article

Brown, L. S. (1993, Spring). My research with oranges. *The Psychology Department Newsletter, 3,* 2.

Sample Citation: Book

American Psychiatric Association. (1990). *Diagnostic and statistical manual of mental disorders* (3rd ed.). Washington, DC: Author.

Booth, W. C., Colomb, G. G., & Williams, J. M. (1995). *The craft of research.* Chicago: University of Chicago Press.

Sample Citation: Chapter or Section in a Book

Stephan, W. G. (1985). Intergroup relations. In G. Lindzey & E. Aronson (Eds.), *The handbook of social psychology* (3rd ed., Vol. 2, pp. 599–658). New York: Random House.

Sample Citation: Web Page

Dewey, R. A. (2004). *APA Style Resources by Russ Dewey.* Retrieved September 8, 2004, from http://www.psywww.com/resource/apacrib.htm