Financial Aid and Student Retention

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Gauging Causality in Discrete-Choice Propensity Score-Matching Models

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Limitations of Higher Education Studies

- Descriptive data
- Inferential data
  - Insufficient covariate controls
  - *Sample selection bias* (restricted observation in dependent variable)
  - *Endogeneity bias* (choice variable correlated with error term)
- Theory development
  - Lack of disciplinary integration
  - Lack of evaluative research

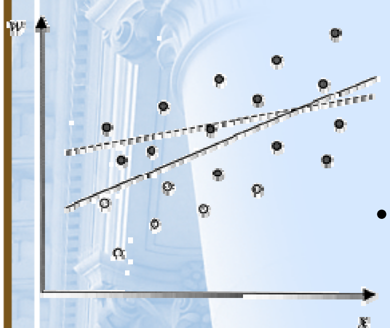
Lack of randomization, experimental design

2

Limitations of Higher Education Studies

- Research on financial aid:
  - Inconsistent findings
  - Unbalanced literature review
  - Methodological and data problems
- Advocacy vs. scholarship? (examples)
  - Congressional Advisory Committee on Student Financial Aid
  - The Education Trust

3



Limitations of Higher Education Studies

- Addressing endogeneity bias in observational studies on treatment effects
  - *Heckman correction* (the two-stage method, Heckman's lambda, Inverse Mill's ratio)
  - *Instrumental variable* (IV) estimation (predictor related to treatment but not outcome)

Assumptions:

1) Normal distribution of error terms in selection and outcome model
2) At least one predictor uncorrelated with outcome

4

Gauging the Financial Aid-Student Success Nexus

- Estimating the influence of aid on freshmen retention at moderately expensive public university
  - Expanding *covariate controls*
  - Correcting *selection bias* in aid status via propensity score-matching
  - *Decomposing treatment* effect of aid via counterfactual analytical framework
  - Underpinning findings with a *plausible paradigm* central to other disciplines

5

Estimating the Influence of Aid on Freshmen Retention

- Analytical process
  1. Identify pre-treatment variables that explain financial aid support to freshmen
  2. Estimate propensity for aid support via multinomial logit/probit model
  3. Match aided vs. unaided on propensity score (identify common support, check for score balance across all variables)
  4. Estimate impact of aid status/propensity for aid on retention via binary logit models with unmatched and matched freshmen (at $\alpha \leq .05$)

6

Data Sources, Cohorts, Model Specifications

- Panel data from institutional student information system, ACT Student Profile Section, CIRP Trends File
- Spring-retained freshmen who entered in fall 2001 through 2005 (N=6,048 or 71%, excl. foreign/athlete students, missing cases)
- Models specified for typical aid packages:
  - Grants/scholarships package vs. no aid (N=3,109)
  - Package with loans vs. no aid (N=2,176)
  - Millennium aid-only students (N=1,226) not tested
- Separate estimates by student capacity to afford cost of attendance (EFC), controlling for net remaining cost and academic experience with hierarchical variable entry

7

Propensity Score Matching

$$P_{ij} = \frac{e^{X_{ij}\beta + Z_i\delta_j}}{\sum_{k=1}^{J} e^{X_{ik}\beta + Z_i\delta_k}}.$$

- Score estimation via multinomial logit model: $\ell^{(r)} = u'\alpha^{(r)} + \omega^{(r)\prime}\delta + \varepsilon^{(r)} = \eta^{(r)} + \varepsilon^{(r)}$, $r = 1,\ldots,k$, with covariate vector $\omega^{(r)}\int$*(income, gender, age, ethnicity/race, prep index, un/declared, test date, AP credits, credit load, housing, facilities use),* where r is a finite choice set
- Unconfoundedness assumption: Treatment (aid) is random conditional on set of observed pre-treatment characteristics ($\omega^{(r)}$), i.e., ignorability of aid selection
- $\int(\omega_i \mid A_i=1, p(\omega_i)=p) = \int(\omega_i \mid A_i=0, p(\omega_i)=p) = \int(\omega_i \mid =p)$ where distribution of ω_i is equal for aided and unaided with matched propensity scores p
- $A \perp y(0), y(1) \mid p(\omega_i)$, where balance in $p(\omega_i)$ is checked for each covariate after matching on p

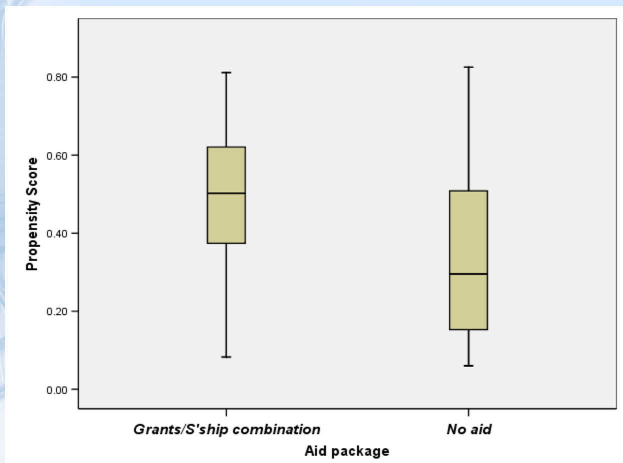
8

Propensity Score Matching

- Matching aided with unaided using stratification with minimum of 5 groups
  - Estimated to remove 90% in bias
  - Preferred if unobservables are suspected
  - Generates more matches with sufficiently large control group (unaided)
  - Alternatives: nearest neighbor, radius, kernel, Mahalanobis-metric matching
- Exclude cases outside common support area, check for balance within stratum, split stratum if unbalanced, repeat until balanced
- Estimate standard errors via bootstrap replications (min. 500-1000)

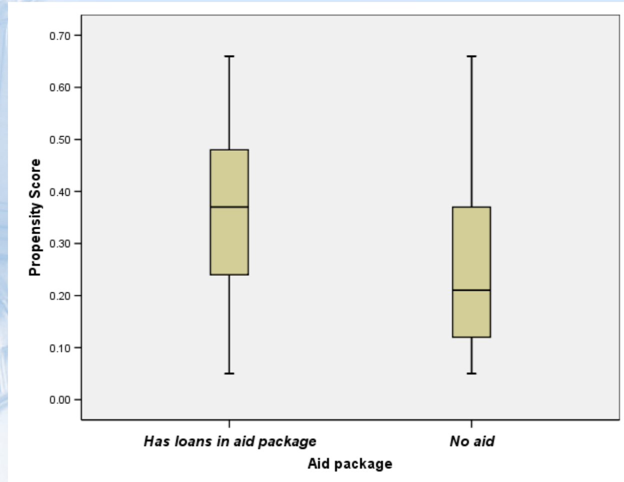
9

The Common Support Area



91-97% of students matched (depending on model) 10

The Common Support Area



83-93% of students matched (depending on model) 11

Propensity Score Balance

Within-Stratum Statistics of New Full-Time Freshmen, 2001-2005							
	Matched Size (N)		Percent Retained			Balance	
With Grants and/or Scholarships (No loans)	No aid	Aided	No aid	Aided	Sig. Diff. (*p* value)	Rejected in X-vector*	Sig. Diff. in Propensity Score (*p* value)
Stratum 1	68	103	76	76	0.91	0	0.16
Stratum 2	52	248	88	78	0.05	0	0.18
Stratum 3	36	305	78	81	0.61	1	0.32
Stratum 4	74	768	86	89	0.50	2	0.95
Stratum 5	99	829	90	90	0.93	2	0.20
Stratum 6	43	288	93	90	0.52	0	0.72
With Loans in Aid Package							
Stratum 1	86	199	81	70	0.04	0	0.76
Stratum 2	109	458	88	82	0.08	0	0.23
Stratum 3	63	290	83	80	0.69	3	0.55
Stratum 4	32	290	75	81	0.39	3	0.30
Stratum 5	35	327	83	79	0.61	3	0.13

* Number of variables based on Bonferroni adjusted *t*-test level

4.2% (5/120) and 9% (9/100) of t-tests at $\alpha \leq .05$ 12

First-Year Financial Aid Profile

Average Aid and Need ($) by Estimated Family Contribution for New FT Fresh., 2001-2005					
		Estimated Family Contribution (EFC)^			
With Grants and/or Scholarships (No loans)	All (N=2,541)	< $4, 015 (N=539)	$4,016 - 9,768 (N=371)	> $9,769 (N=873)	Unkown (N=758)
Low-income federal grants	469	2,212	0	0	0
Low-income state grants	119	223	471	9	0
Low-income institutional grants	77	129	287	22	0
Other grants	189	146	117	215	226
Millennium scholarship	2,003	1,881	2,132	1,965	2,070
Other merit-based aid	2,146	2,270	2,471	2,280	1,745
Need after EFC*	4,225	11,945	9,019	1,075	118
Need after all awarded aid*	2,007	6,053	4,179	309	23
With Loans in Aid Package	(N=1,563)	(N=434)	(N=428)	(N=689)	(N=12)
Low-income federal grants	809	2,910	5	0	0
Low-income state grants	243	370	475	24	0
Low-income institutional grants	241	320	398	97	0
Other grants	164	130	222	152	0
Millennium scholarship	1,397	1,365	1,474	1,366	1,631
Other merit-based aid	1,024	1,154	974	983	490
Unsubsidized loans	3,560	1,284	2,483	5,652	9,128
Subsidized loans	1,760	2,812	2,532	648	0
Need after EFC*	8,115	15,320	10,198	2,159	15,142
Need after all awarded aid*	2,895	5,787	3,778	496	4,562

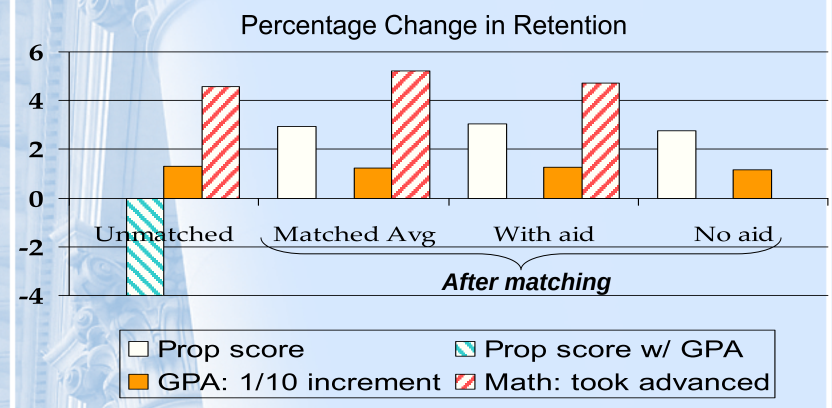
* Based on total cost of attendance per federal aid application information (FAFSA), ^constant 2005-$

Statistical Results: Reference Example

Parameter Estimates of Second-Year Enrollment of New Full-Time Freshmen with Grants/Scholarships (No Loans), 2001-2005												
	Unmatched			Matched Avg Effect			Matched Avg Treated			Matched Avg Untreated		
Percentage change in probability of second-year enrollment: [1]		Δ - p	Sig.		Δ - p	Sig.		Δ - p	Sig.		Δ - p	Sig.
All *(Unmatched N = 3,109)*												
Received grant/scholarship (unmatched); propensity score (matched)			NS		2.94	***		3.06	***		2.76	**
Controlling for first-year GPA and math experience												
Received grant/scholarship (unmatched); propensity score (matched)		-3.99	*			NS			NS			NS
GPA (1/10 of one letter grade increment)		1.31	***		1.22	***		1.27	***		1.15	***
Math experience[2]	Adv	4.58	*	Adv	5.20	**	Adv	4.73	*			
% of cases matched				93.67								

Percentage change in second-year retention probability using a linear transformation of the log odds (*p*[1-p]*β)*

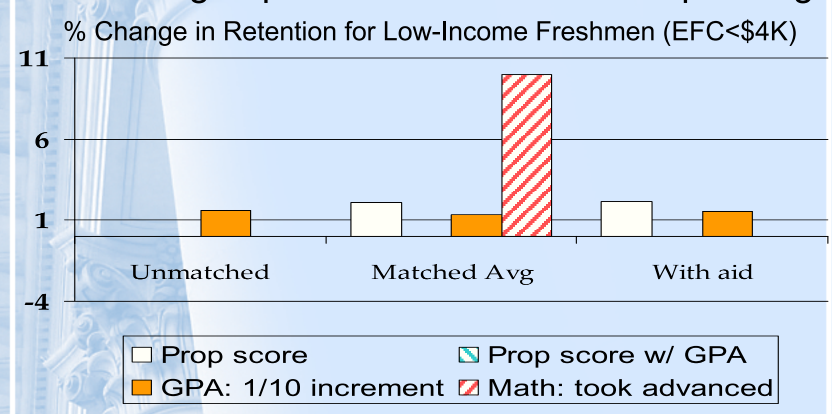
Estimating Impact of Grants/Scholarships Pckg



- Propensity to receive gift aid has no bearing on retention
- Negative endogeneity bias net of first-year academic experience.
- *But, no statistical control for student ability to pay and assume unmet need!*

15

Estimating Impact of Grants/Scholarships Pckg

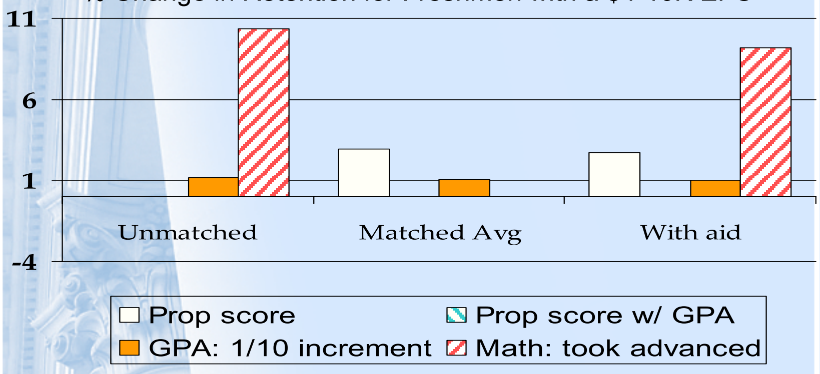


- Propensity to receive gift aid has no bearing on retention, net of academic experience *(no significant GPA/prop score interaction)*
- No significant correlation with amount and type of aid
- Positive correlation with advanced math (10%) and GPA

16

Estimating Impact of Grants/Scholarships Pckg

% Change in Retention for Freshmen with a $4-10K EFC

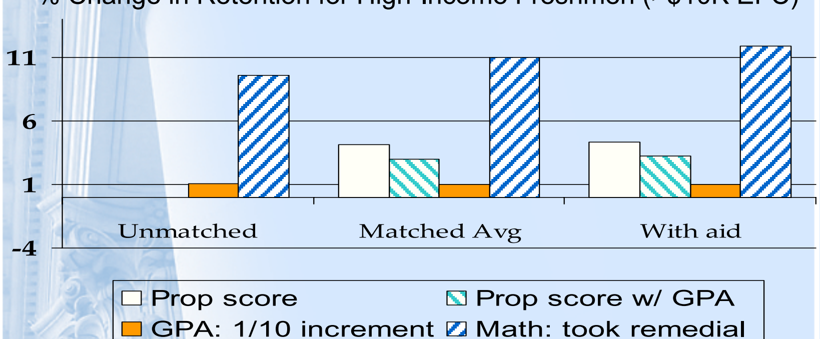


- Propensity to receive gift aid has no bearing on retention, net of academic experience
- No significant correlation with amount and type of aid
- Positive correlation with advanced math ($\alpha < .10$) and GPA

17

Estimating Impact of Grants/Scholarships Pckg

% Change in Retention for High-Income Freshmen (>$10K EFC)

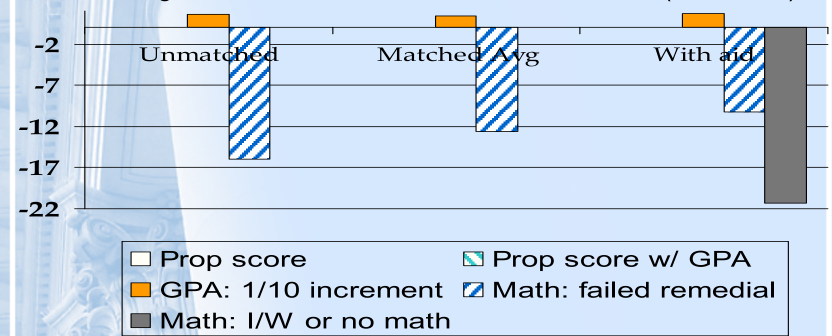


- Propensity to receive gift aid shows a positive correlation, net of academic experience
- Overall and endogeneity bias detected, largely unaffected by the amount of aid (3.26 vs. 3.01)
- Remedial math students exhibit greater persistence (12%)

18

Estimating Impact of Aid Package with Loans

% Change in Retention for Low-Income Freshmen (EFC<$4K)

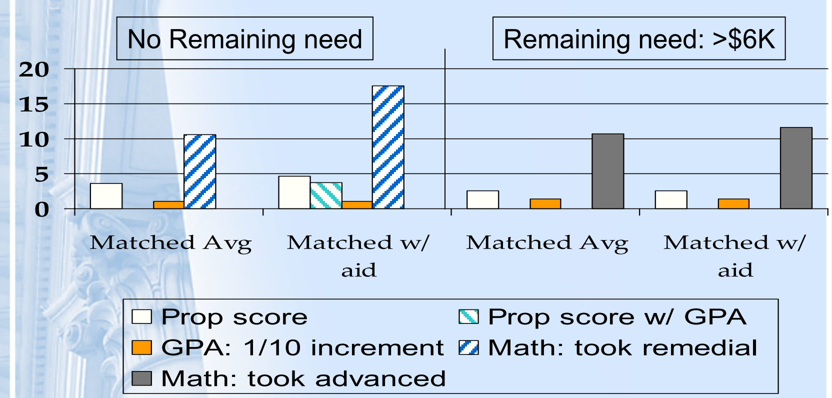


- Propensity to receive aid and amount/type of aid shows no correlation after factoring in academic experience
- Remedial math students and those not completing math in the first year face elevated dropout risk (α <.05 and <.10, respectively)
- Similar results for other EFC students as with gift aid-only pckg

19

Estimating Impact of Grants/Scholarships Pckg

% Change in Retention by Remaining Need after EFC



- Gift aid benefit for those ineligible for need-based aid
- No gift aid benefit, but math-related benefit, for the needy

20

Findings

- Pattern of correlations suggests:
  - Financial aid-retention nexus depends on need level and academic experience
  - Endogeneity associated with aid status biases results from non-randomized data
  - Had aided high-EFC students not received gift aid, their retention would be less likely
  - Low-income/EFC students accrue retention benefits from academic success
  - High-income/EFC students accrue retention benefits from financial aid

21

Findings

- Thus:
  - Allocating more aid to higher-income freshmen (EFC >$4K) *coupled* with better preparation of, academic assistance to low-income freshmen would maximize overall retention
- Results are consistent with economic theory of moral hazard
  - Utility maximization is compromised under uncertainty arising from asymmetry of information between benefactor and beneficiary

22

Moral Hazard Theory

- Motivation to excel academically is undermined due to:
  - Low cost of potential failure (i.e., investment risk)
  - Financial aid that is ascribed, not earned (e.g., need-based vs. merit-based)
  - Lack of effective monitoring of academic progress (e.g., by supportive parents)

- Intellectual foundation:
  - Mirrlees, J. A. (1999). The theory of moral hazard and unobservable behavior: Part I. *Review of Economic Studies* 66(1): 3-21. [1996 Nobel laureate in Econ.]
  - Arrow, K. J. (1968). The economics of moral hazard: further comment. *The American Economic Review* 58(3): 537-539. [1972 Nobel laureate in Econ.]
  - Pauly, M. V. (1968). The economics of moral hazard: comment. *The American Economic Review* 58(3): 531-537.

Corroborating research

1. Bodvarsson, O. B., and Walker, R. L. (2004). Do parental cash transfers weaken performance in college? *Economics of Education Review* 23: 483-495
2. Long, N. V., and Shimomura, K. (1999). Education, moral hazard, and endogenous growth. *Journal of Economic Dynamics and Control* 23(5-6): 675-698.
3. Davila, A., and Mora, M. T. (2004). The scholastic progress of students with entrepreneurial parents. *Economics of Education Review* 23: 287-299.
4. Keane, M. P. (2002). Financial aid, borrowing constraints, and college attendance: evidence from structural estimates. *The American Economic Review* 92(2): 293-297.
5. Cameron, S. V., Heckman, J. J. (1998). Life cycle schooling and dynamic selection bias: models and evidence for five cohorts of American males. *Journal of Political Economy* 106(2): 262-333.
6. Stinebrickner, T. R., and Stinebrickner, R. (2004). *Credit Constraints and College Attrition.* Paper presented at the Canadian Employment Research Forum, Ryerson University, Toronto, Ontario, June 3-4.

Propensity Score-Matching

- Aim is to control for confounding when evaluating treatment effect (e.g. impact of aid, advising, learning communities) to approximate randomization
- Preferred with infrequent outcome, common treatment, and many covariates
- Scalar summary of pre-treatment observables allows shrinkage of high-dimensional model
- Over-parametrization is not an issue in score estimation
- Distributional balance of covariates within strata, subclasses, or pairs is key (e.g., check interaction and quadratic terms in scoring model)
- *Principal limitation*: omitted variables strongly related to outcome and uncorrelated with propensity score

25

Propensity Score-Matching

- Intellectual foundation:
  - Rosenbaum, P. R., and Rubin, D. B. (1983). The central role of the propensity score in observational studies for causal effects. *Biometrika* 70(1): 51-55.
  - Rosenbaum, P. R., and Rubin, D. B. (1984). Reducing bias in observational studies using subclassification on propensity score. *Journal of the American Statistical Association* 79(387): 516-524.
  - Dehejia, R. H., and Wahba, S. (2002). Propensity score-matching methods for non-experimental causal studies. *The Review of Economics and Statistics* 84(1): 151-161.
  - Rosenbaum, P. R. (2002) *Observational Studies*, 2nd ed. New York: Springer.

26

Standards of Evidence

- Analytical quality of research
- Familiarity with other disciplines
  - Economics
  - Medicine
  - et al.
- Money and education
  - Adelman, C. (2007). Do we really have a college access problem? *Change* (July-August): 48-51.

Link to presentation and paper:
http://www.cis.unr.edu/IA_Web/research.aspx

27