You're Going to Miss Me When I'm Gone: How Mobility Affects Earnings Measurement in States

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Any opinions and conclusions expressed herein are those of the authors and do not necessarily represent the views of the U.S. Census Bureau. These results have been reviewed to protect confidentiality. (DRB Requests #DRB-B0007-CED-20181029, DRB-B0033-CED-20190318, and DRB-B0064-CED-20190703)

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- We are developing a method to correct for this bias.

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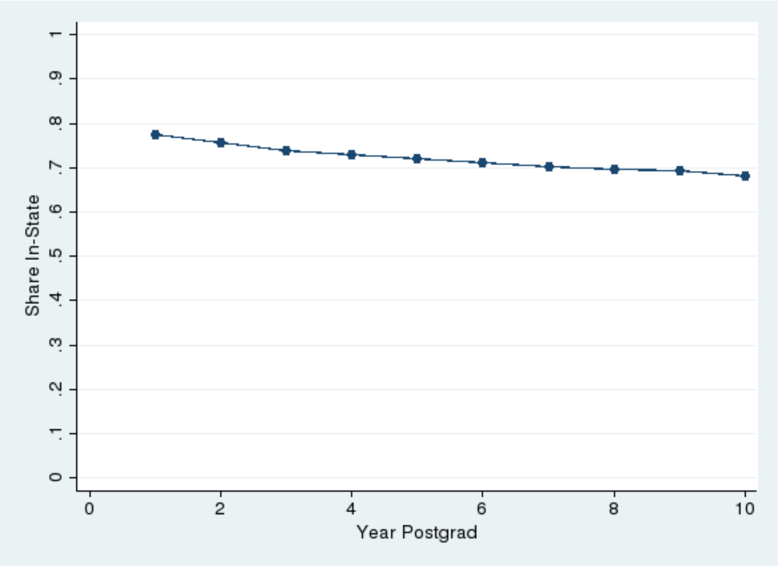
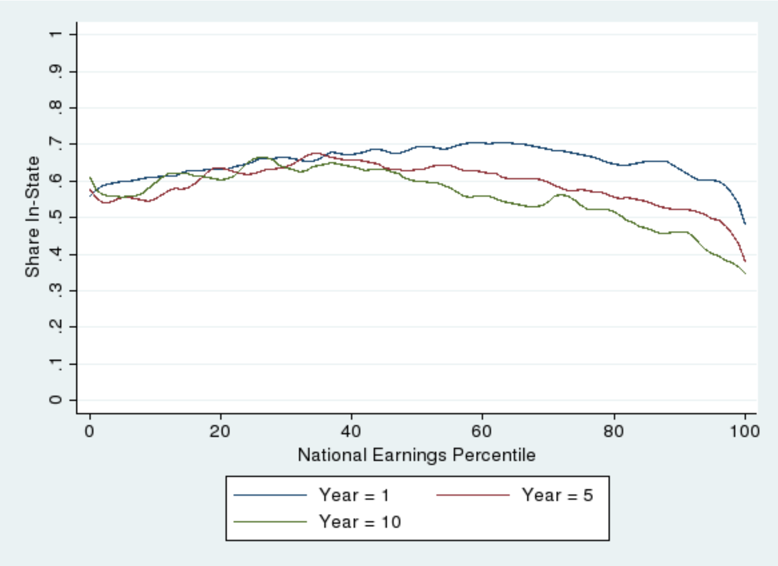
Data

- Administrative records of bachelors recipients from University of Texas Systems (2001-2015)
- LEHD earnings data, which is sourced from 50 states and the District of Columbia; includes all employment covered by unemployment insurance (2001-2016)
- In the following graphs, we restrict to observations with national earnings above $10,000 and at least three quarters of employment in the calendar year.

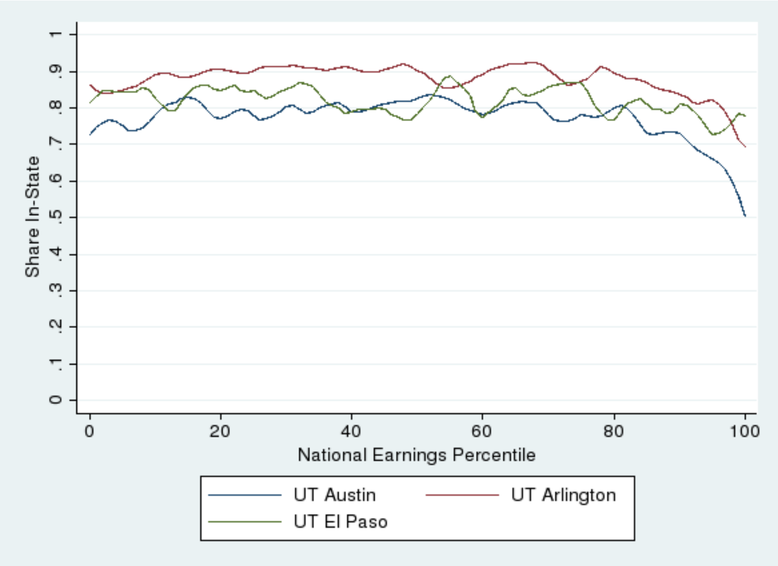
Share of Employed Graduates In-State



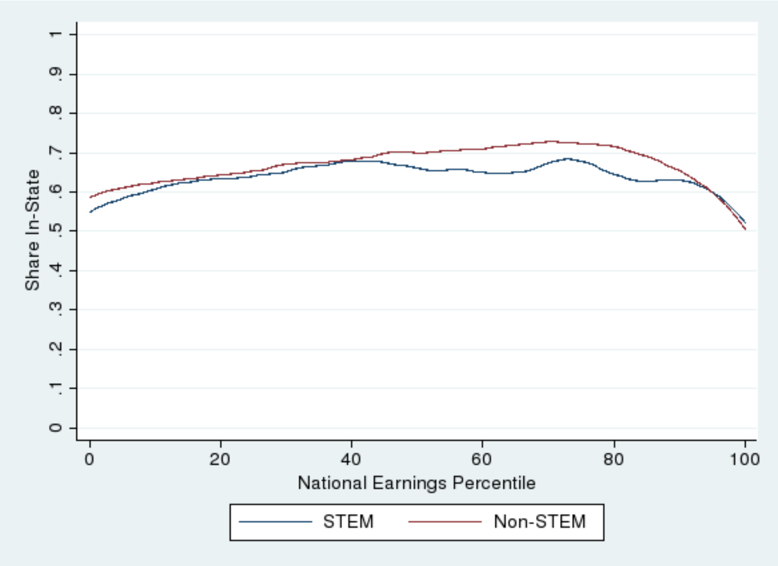
Mobility by Year Post-Graduation



Mobility by Institution, 1 Year Post-Grad

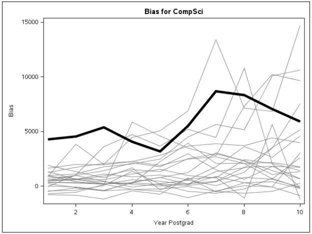


Mobility by STEM



Bias by Major

Computer Science



Engineering

Psychology

Business

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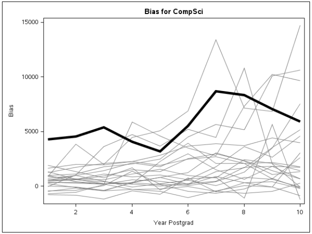

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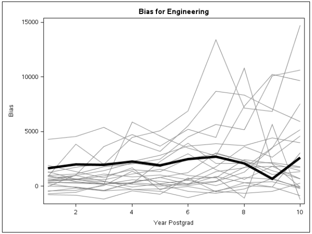

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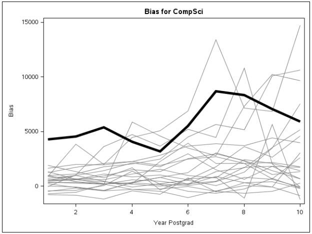

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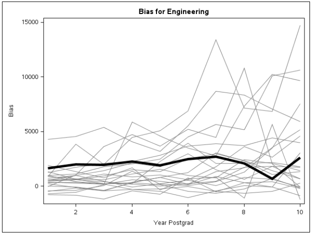

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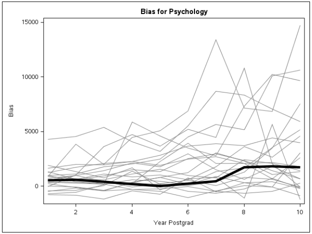

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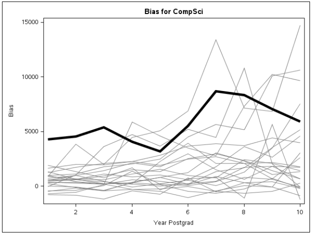

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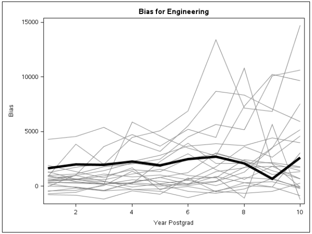

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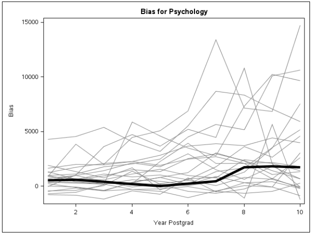

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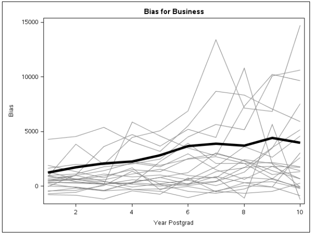

Empirical Application

Andrews, Li and Lovenheim (2016) want to measure how college quality affects earnings.
Basic regression:

$$\mathrm{Earnings_{it}} = \beta \mathrm{Flagship_i} + \Theta \mathrm{X_{it}} + \epsilon_{\mathrm{it}}$$

Their paper only has access to Texas UI wage data, drops anyone who doesn't have sufficient earnings in-state.

	Fixed Effects			Demographics		
	In-State	National	Bias	In-State	National	Bias
Full Sample	-719.3	2070	2790	-938.8	1619	2557
	(102.2)	(128.7)		(103.6)	(128.9)	
Earn > 0	2746	3465	719	2058	2795	737
	(137.6)	(147.0)		(136.2)	(149.0)	
Log(Earnings)	0.0867	0.110	0.0236	0.0526	0.0776	0.0250
	(0.0074)	(0.247)		(0.0074)	(0.0066)	
P25 Log	0.0568	0.0737	0.0169	0.0325	0.0491	0.0166
	(0.0022)	(0.0019)		(0.0022)	(0.0020)	
P50 Log	0.1043	0.1246	0.0203	0.0689	0.0917	0.0228
	(0.0014)	(0.0012)		(0.0014)	(0.0012)	
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