The Returns to College(s): Estimating Value-Added and Match Effects in Higher Education

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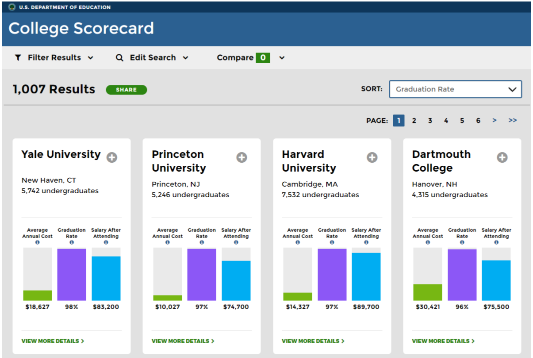
Disclaimer

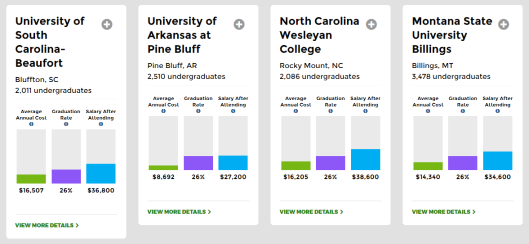
The conclusions of this research do not necessarily reflect the opinions or official position of the Texas Education Research Center, the Texas Education Agency, the Texas Higher Education Coordinating Board, the Texas Workforce Commission, or the State of Texas.

Motivation

- Enrolling in college tends to pay off for marginal students
  E.g. Card (2001); Lemieux and Card (2001); Carneiro et al. (2011); Angrist and Chen (2011); Zimmerman (2014); Heckman et al. (2018); Mountjoy (2019)
- But for the college-bound, choice is not whether to enroll, but *where*
- Is college college? Or does it matter *which* college?

Motivation


U.S. DEPARTMENT OF EDUCATION
College Scorecard
Filter Results
Edit Search
Compare 0
1,007 Results
SHARE
SORT:
Graduation Rate
PAGE: 1 2 3 4 5 6 > >>
Yale University
New Haven, CT
5,742 undergraduates
Average Annual Cost
Graduation Rate
Salary After Attending
$18,627 98% $83,200
VIEW MORE DETAILS
Princeton University
Princeton, NJ
5,246 undergraduates
$10,027 97% $74,700
VIEW MORE DETAILS
Harvard University
Cambridge, MA
7,532 undergraduates
$14,327 97% $89,700
VIEW MORE DETAILS
Dartmouth College
Hanover, NH
4,315 undergraduates
$30,421 96% $75,500
VIEW MORE DETAILS


University of South Carolina-Beaufort
Bluffton, SC
2,011 undergraduates
Average Annual Cost
Graduation Rate
Salary After Attending
$16,507 26% $36,800
VIEW MORE DETAILS
University of Arkansas at Pine Bluff
Pine Bluff, AR
2,510 undergraduates
$8,692 26% $27,200
VIEW MORE DETAILS
North Carolina Wesleyan College
Rocky Mount, NC
2,086 undergraduates
$16,205 26% $38,600
VIEW MORE DETAILS
Montana State University Billings
Billings, MT
3,478 undergraduates
$14,340 26% $34,600
VIEW MORE DETAILS

This Paper

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4. **Does value-added vary across students? (Mis)match effects?**
   - Estimate heterogeneous college VA by student observables
   - Race, income, gender, "cognitive" & "non-cognitive" skills

Challenges

- **Big data**
  - College-specific treatment effects require many students & schools
- **Rich data**
  - Need to link high school $\rightarrow$ college $\rightarrow$ degrees $\rightarrow$ earnings
- **Identification**
  - Endogenous applications & admissions invite massive selection bias

Solutions

- **Data**: linked administrative records spanning the Texas population
  - All TX public high school grads across all TX public universities
  - Link high school records, college records, and earnings by SSN
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- **Identification**: proxy for unobservables using admissions portfolios
  - High-dimensional 2-layer signal of ability, ambition, advantage
  - Variations on this "matched applicant" theme:
    Dale and Krueger (2002, 2014); Fryer and Greenstone (2010); Cunha and Miller (2014); Arcidiacono et al. (2016); Abdulkadiroglu et al. (2020)
  - Our implementation: FEs for every distinct portfolio of apps & admits

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  - Our implementation: FEs for every distinct portfolio of apps & admits
- **Validation**: battery of empirical exercises to probe validity
  - Covariate balance across college treatments within portfolios
  - VA estimates impervious to all available additional controls
  - Typical strategies appear to substantially under-correct for selection

Contributions

- Estimating labor market returns to college selectivity/ "quality"
  Hunt (1963); Wise (1975); Brewer et al. (1999); Dale and Krueger (2002, 2014); Hoekstra (2009); Black and Smith (2004, 2006); Long (2008, 2010); Andrews et al. (2016); Ge et al. (2018); Bodoh-Creed and Hickman (2019); Black et al. (2020)

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→ Also build on Black and Smith (2006): other dimensions of college quality

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- Examining outcomes across individual colleges using admin data
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→ Teacher VA: meaningful differences not captured by observable "quality" measures

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- Testing for mismatch in education
  Bowen and Bok (2000); Sander and Taylor (2012); Arcidiacono et al. (2016); Arcidiacono and Lovenheim (2016); Dillon and Smith (2018); Angrist et al. (2019)

→ Natural application of our research design & high-quality admin data, including earnings

→ Our approach naturally answers related questions too: mobility, supermodularity

Limitations

- Our variation is limited to
  - Choices among 4-year colleges
  - By inframarginal admitted students
  - Enjoying multiple admission offers
  - In the Texas public sector
- Other important margins involve different students, counterfactuals
  - Marginally qualified applicants crossing a minimum cutoff

    Hoekstra (2009); Zimmerman (2014); Goodman et al. (2017)
  - Fancy privates, questionable for-profits, CCs, no college at all

    Cohodes and Goodman (2014); Cellini and Turner (2019); Mountjoy (2019)
  - Intervening early enough to transform fundamental college ambitions

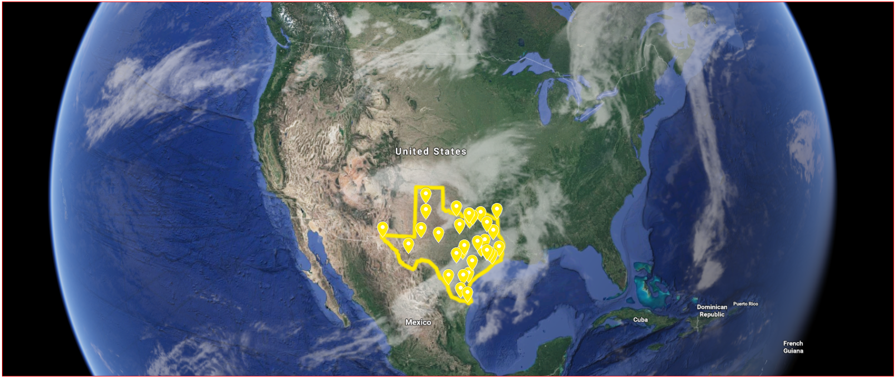
    Hoxby & Turner (2013), Bodoh-Creed & Hickman (2019), Dynarski et al. (2020)
- Causal consequences at distinct junctures in the U.S. college pipeline

Today's Agenda

- ✓ Introduction
- **Setting & Data**
- Research Design
- VA Estimates & Validation
- Distributional Magnitudes
- Institutional Predictors
- Potential Mechanisms
- Match Effects
- Conclusion

Data Setting: Texas

- 2nd largest U.S. state, population 29 million
- 10th largest economy in the world
- 30+ public universities enrolling 726,000 students



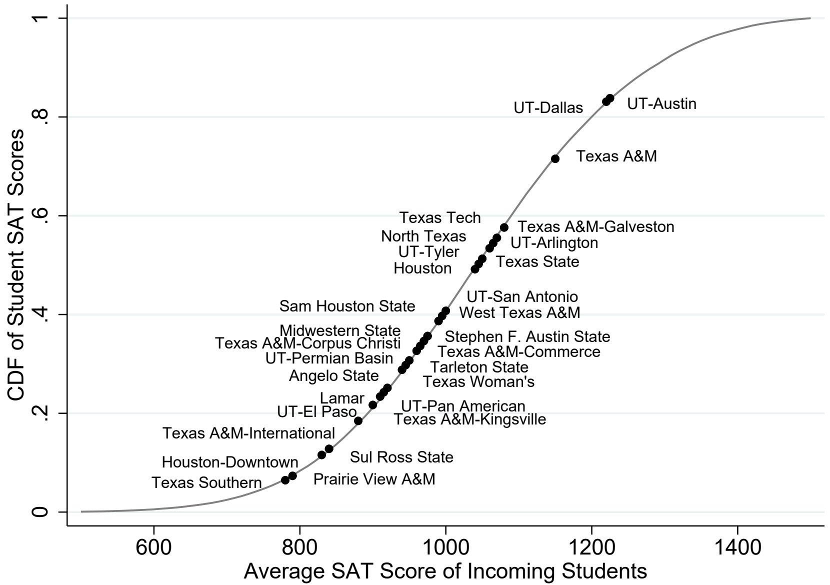
Data: Linked Administrative Records

- All public high school graduates in Texas (1999-2008 cohorts)
  - Demographics (gender, race, free/reduced price lunch, HS location)
  - Academic achievement (test scores, rigor of HS coursework, top 10%)
  - "Non-cognitive" measures (daily attendance, disciplinary infractions)
- Applications and admissions decisions at all Texas public universities
  - Form each student's exact portfolio of applications & admissions
- Enrollments and degrees at all Texas public (& private) universities
  - Persistence (years completed)
  - Transfer
  - BA completion (by year 4, 6, 8...)
  - Major (STEM indicator)
- Quarterly earnings records for all Texas employees
  - Directly from state UI tax records
  - Industry (oil & gas indicator)

Data: Summary Statistics

	Mean	(SD)		Count	Share
Covariates			*Treatments*		
Female	.544		Texas A&M (TAMU)	54,953	.13
Low-income (FRPL)	.241		UT-Austin	52,508	.124
Black	.121		Texas Tech	32,371	.077
Hispanic	.227		UT-San Antonio	27,569	.065
10th grade test score (std.)	0	(1)	North Texas	24,146	.057
High school attendance (std.)	0	(1)	Texas State-San Marcos	23,686	.056
			Houston	23,528	.056
Applications			Stephen F. Austin State	17,372	.041
Applied to 1 school	.601		Sam Houston State	15,704	.037
Applied to 2 schools	.233		UT-Pan American	15,000	.035
Applied to 3 schools	.104		UT-Arlington	14,595	.035
Applied to 4 schools	.041		UT-El Paso	14,361	.034
Applied to 5+ schools	.022		Angelo State	10,585	.025
			Lamar	10,569	.025
Admissions			Tarleton State	9,795	.023
Admitted to 1 school	.691		TAMU-Corpus Christi	8,550	.02
Admitted to 2 schools	.212		Texas Southern	7,736	.018
Admitted to 3 schools	.069		Prairie View A&M	7,353	.017
Admitted to 4 schools	.02		TAMU-Kingsville	6,675	.016
Admitted to 5+ schools	.009		West Texas A&M	6,498	.015
			UT-Dallas	6,453	.015
Academic Outcomes			Midwestern State	5,873	.014
Ever transfer	.271		Houston-Downtown	5,196	.012
Years of college completed	2.89	(1.52)	TAMU-Commerce	4,293	.01
BA within 4 years	.274		Texas Woman's	4,001	.009
BA within 6 years	.592		TAMU-International	3,537	.008
BA within 8 years	.652		UT-Tyler	3,248	.008
STEM degree	.13		TAMU-Galveston	2,797	.007
			Sul Ross State	2,037	.005
Earnings Outcomes			UT-Permian Basin	1,963	.005
Has positive earnings	.848				
Annualized earnings	44,834	(28,485)			
	Observations	422,956			

Data: College Selectivity Distribution



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Potential Outcomes Framework

- Potential outcome for student i at counterfactual college j:

$$Y_{ij} = \overbrace{\underset{\substack{\text{Constant}\\\text{(Normalization)}}}{\mathbb{E}[Y_{ij}]}}^{\kappa} + \overbrace{\underset{\substack{\text{School fixed effect}\\\text{(Value-added)}}}{\mathbb{E}_{i\in\mathcal{I}}[Y_{ij}] - \kappa}}^{\nu_j} + \overbrace{\underset{\substack{\text{Student fixed effect}\\\text{(Ability, ambition, advantage)}}}{\mathbb{E}_{j\in\mathcal{J}}[Y_{ij}] - \kappa}}^{\alpha_i} + \overbrace{\underset{\substack{\text{Residual}\\\text{(Idiosyncratic match)}}}{Y_{ij} - \kappa - \nu_j - \alpha_i}}^{\epsilon_{ij}}$$

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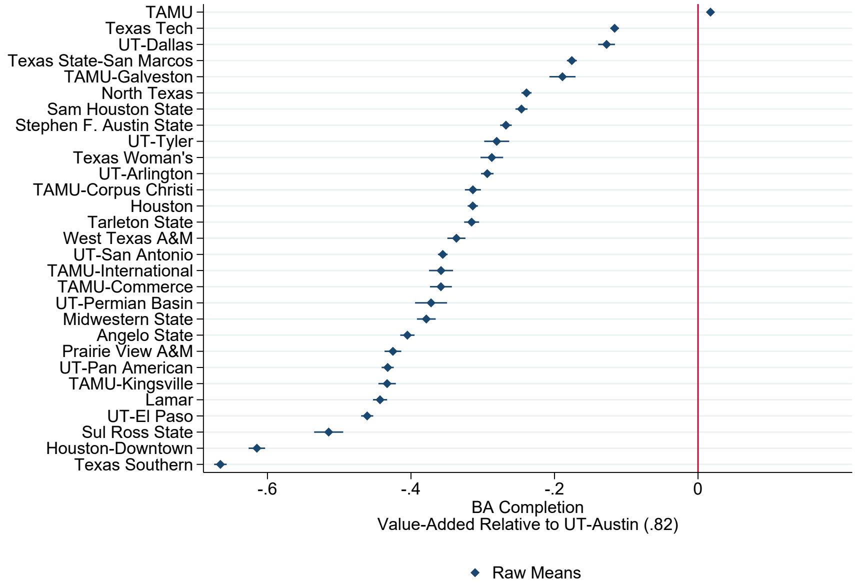
- Two different threats to identification from observational comparisons:

$$\mathbb{E}[Y_i|D_{ij}=1]-\mathbb{E}[Y_i|D_{i0}=1] = \underbrace{\nu_j-\nu_0}_{\text{Causal value-added of } j \text{ vs. } 0}$$

$$+ \underbrace{\mathbb{E}[\alpha_i|D_{ij}=1]-\mathbb{E}[\alpha_i|D_{i0}=1]}_{\text{Vertical selection bias}} + \underbrace{\mathbb{E}[\epsilon_{ij}|D_{ij}=1]-\mathbb{E}[\epsilon_{i0}|D_{i0}=1]}_{\text{Differential match bias}}$$

Raw Means: BA Completion



Threat 1: Vertical Selection Bias

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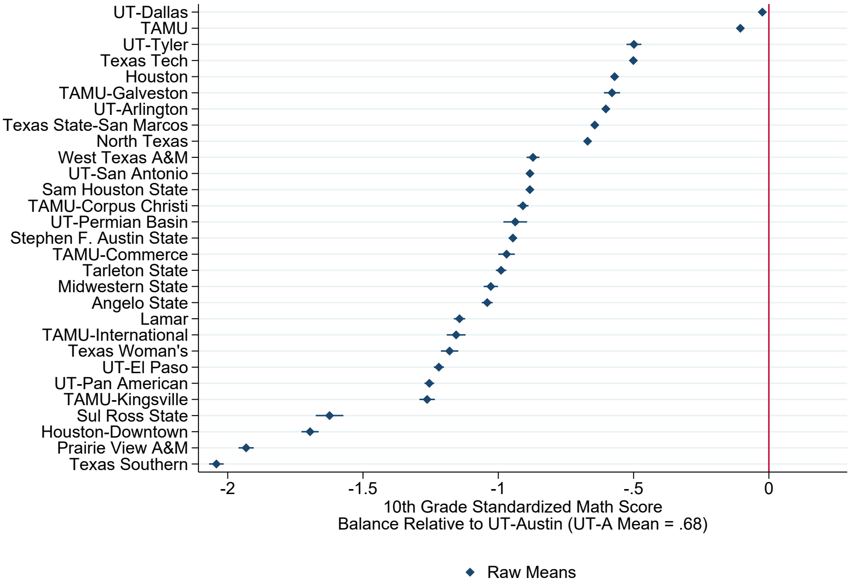
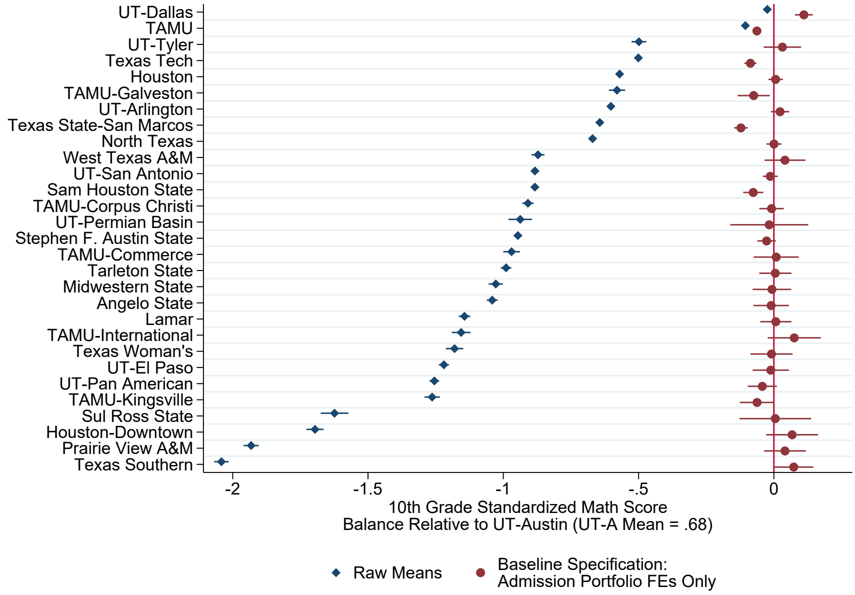
Vertical Selection Bias: 10th Grade Test Scores



Vertical Selection Bias: *Within* Admission Portfolios



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- Assumption 1: No vertical selection bias *within* admission portfolios
  - We will further test this shortly

Threat 2: Differential Match Bias

- Potential outcome for student i at counterfactual college j:

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Differential Match Bias: Canon, Theory, Evidence

- Value-added canon (teachers, schools, neighborhoods):
  - Eliminate match effects from the model entirely: $\epsilon_{ij} \equiv 0 \;\; \forall j \in \mathcal{J}$
  - Or grant them a simple life as orthogonal errors: $\{\epsilon_{ij}\}_{j \in \mathcal{J}} \perp\!\!\!\perp \{D_{ij}\}_{j \in \mathcal{J}}$
  - Somewhat stronger than necessary: symmetric sorting allowed

- We will test for match effects: college x covariate interactions
  - We find little scope for match effects in explaining student outcomes
  - VA estimates for average student are robust to including interactions

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- Assumption 2: No differential match bias within admission portfolios
  - Implicit in the canon; we will directly investigate match effects in a bit

Identification and Implementation

- Derive baseline regression specification from model primitives:

$$
\begin{aligned}
Y_i &= Y_{i0} + \sum_{j\neq 0}(Y_{ij} - Y_{i0})D_{ij} \\
&= \kappa + \nu_0 + \sum_{j\neq 0}(\nu_j - \nu_0) + \alpha_i + \sum_{j}\epsilon_{ij}D_{ij} \\
&= \ddot{\kappa} + \sum_{j\neq 0}\tilde{\nu}_j D_{ij} + \sum_{p\neq 0}\ddot{\phi}_p A_{ip} + \ddot{\epsilon}_i
\end{aligned}
$$

- Under Assumptions 1 & 2, $\ddot{\epsilon}_i$ is mean independent of regressors

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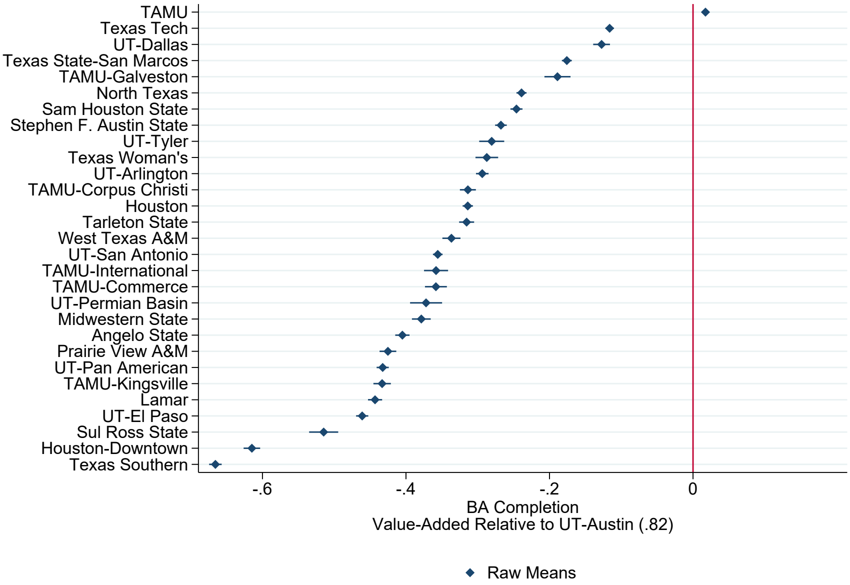
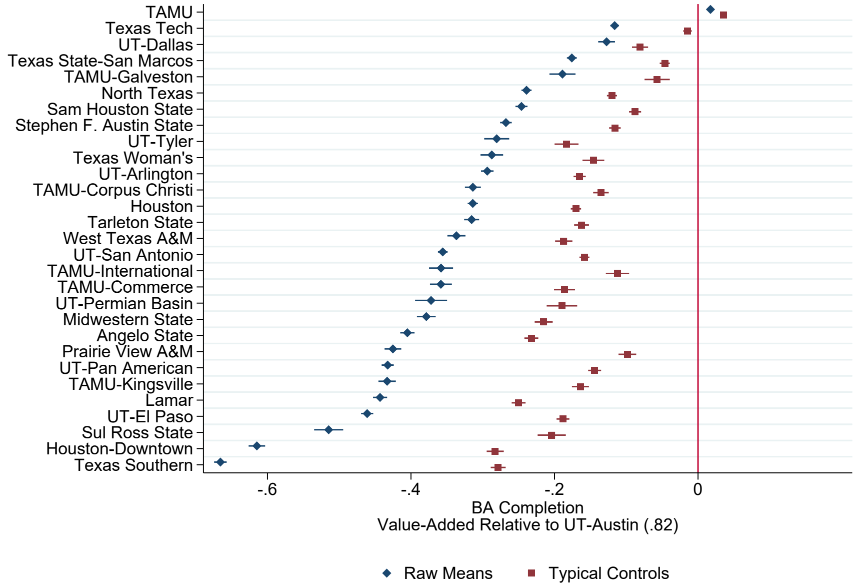
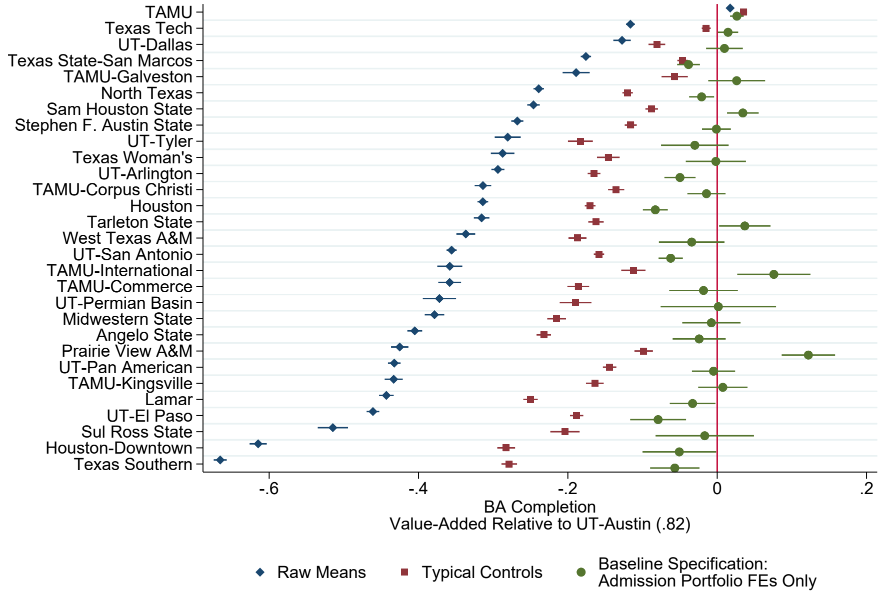


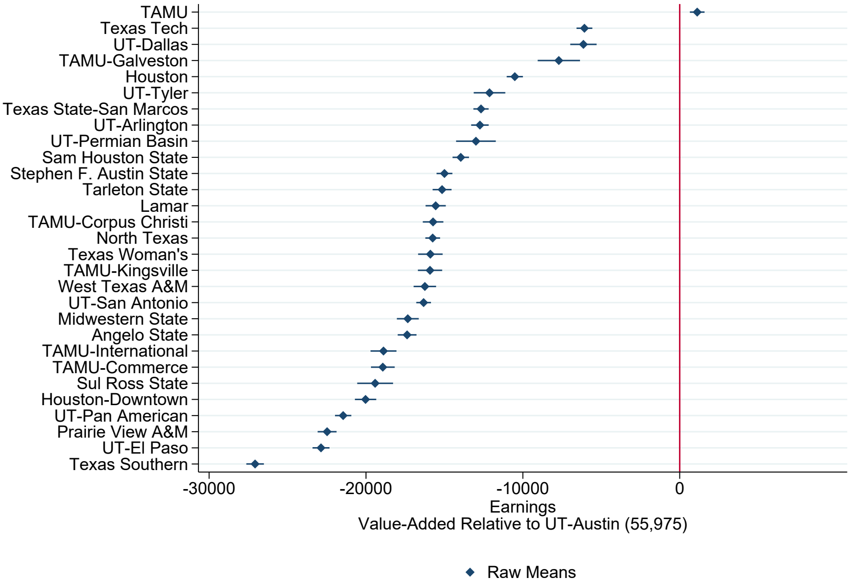
Typical Controls: BA Completion



Baseline Value-Added: BA Completion



Raw Means: Earnings



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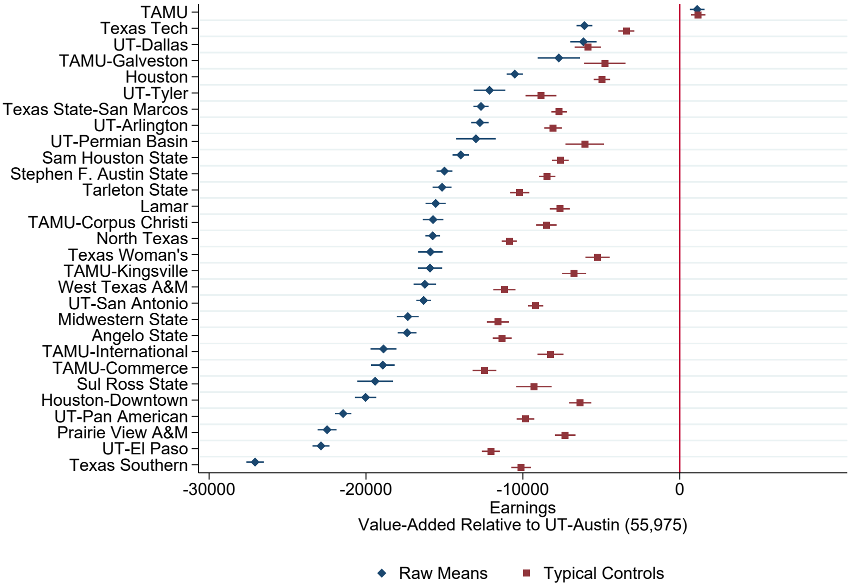

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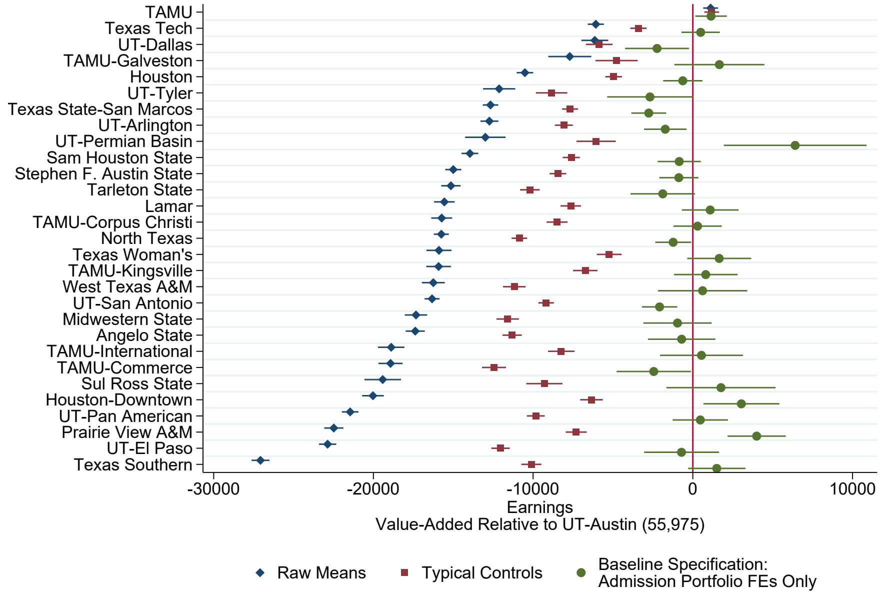
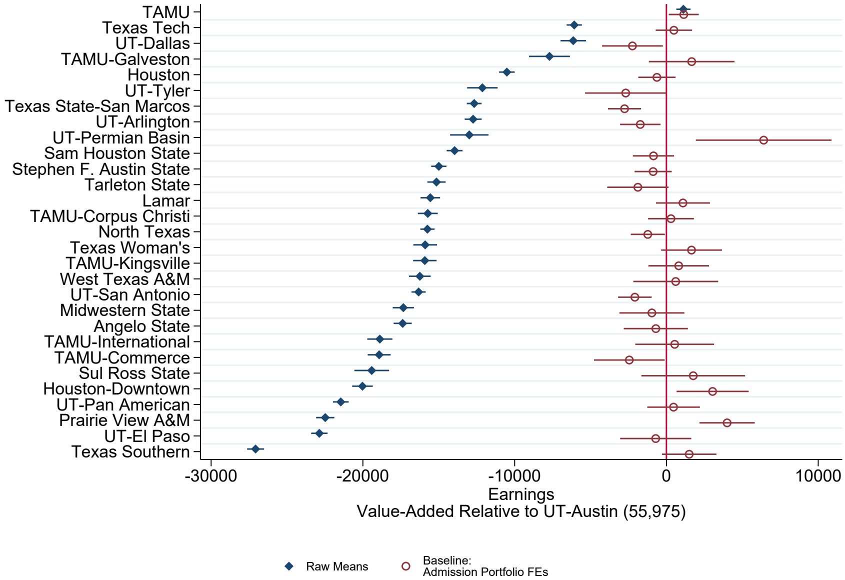


Validating the Matched Applicant Approach: OVB



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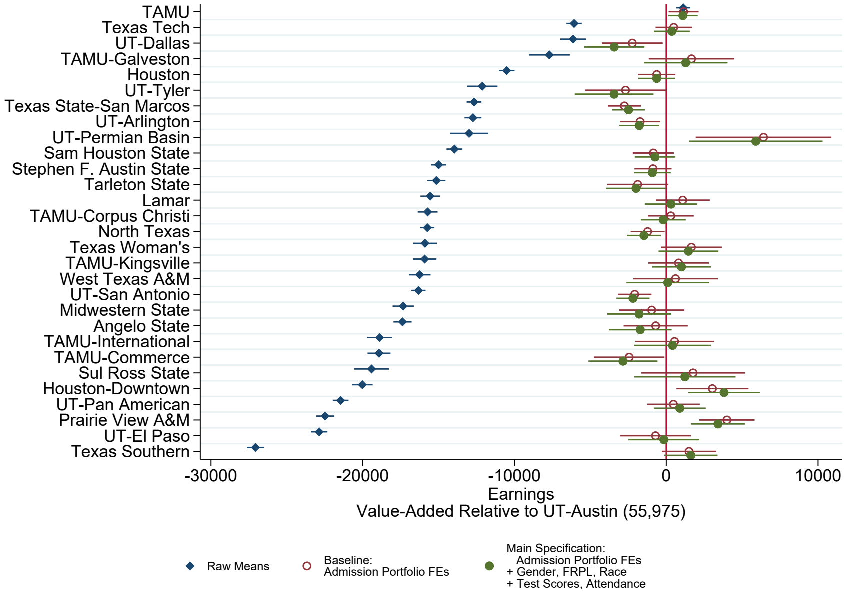

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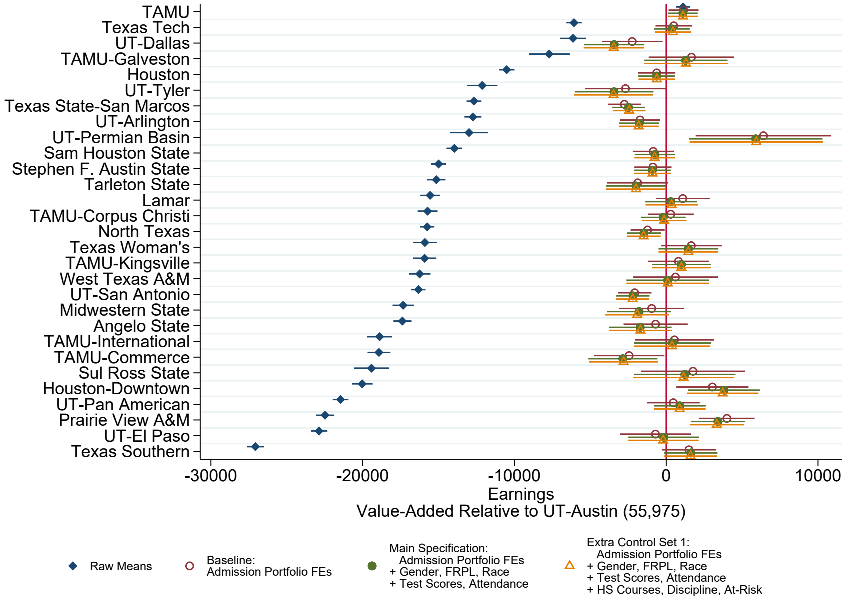

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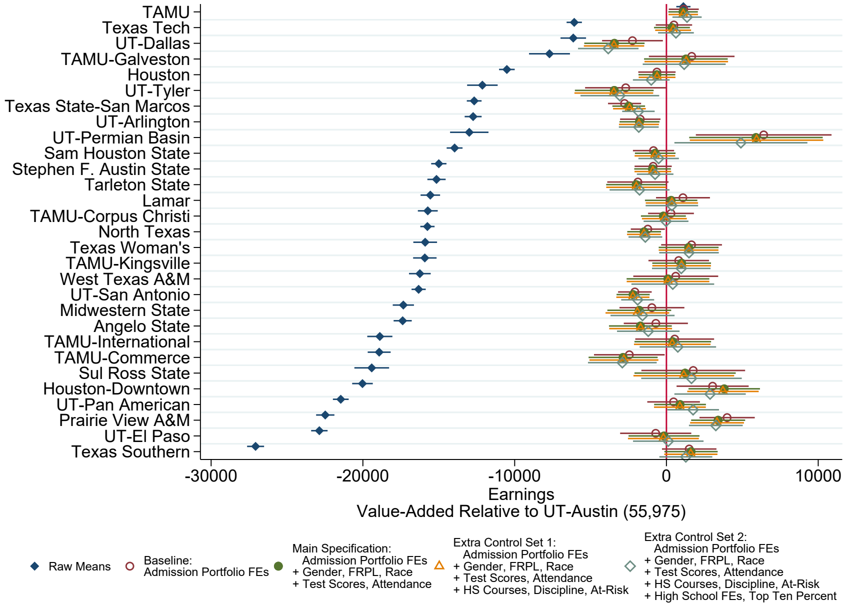
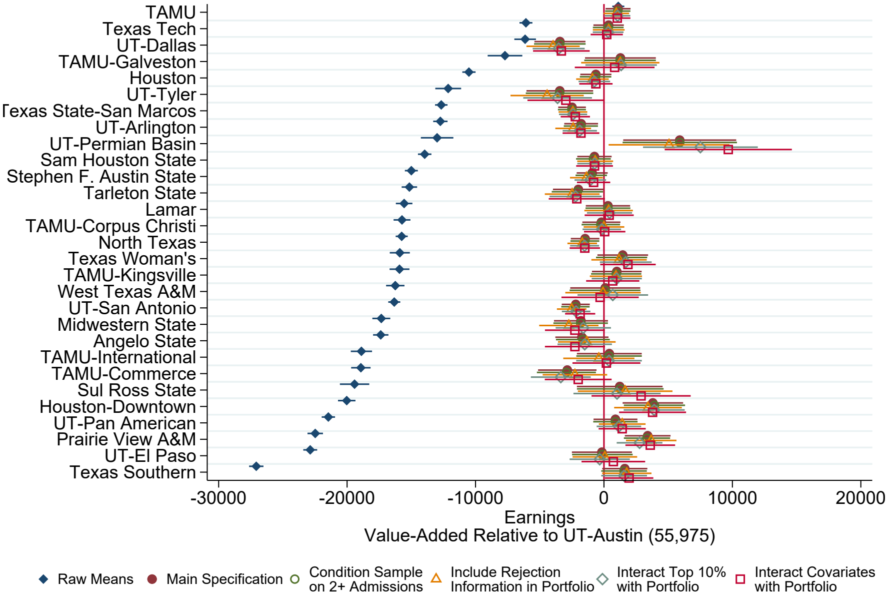


Additional Checks: Richer Portfolio Specifications



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- ✓ Introduction
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- **Distributional Magnitudes**
- Institutional Predictors
- Potential Mechanisms
- Match Effects
- Conclusion

Distributional Magnitudes of VA Across Colleges

- Accounting for estimation error in the distribution of value-added:

$$\sigma^2_{estimates} = \sigma^2_{signal} + \sigma^2_{noise}$$

	BA Completion	Earnings
Panel A: Raw Outcome Means		
Standard deviation of estimates across colleges	.179	8,070
Standard deviation of signal component	.179	8,065
Standard deviation of noise component	.004	276
Panel B: Causal Value-Added Estimates		
Standard deviation of estimates across colleges	.039	1,530
Standard deviation of signal component	.037	1,332
Standard deviation of noise component	.012	753
Panel C: Relationships between Raw Outcome Means and Value-Added		
Signal SD of causal value-added ÷ signal SD of raw outcome means	.207	.165
Correlation of VA estimate with raw outcome mean (uncorrected for noise)	.471	.176
Correlation of signal VA with raw outcome mean (corrected for noise)	.495	.203
Regression of school's value-added estimate on its raw outcome mean (SE)	.103 (.036)	.033 (.035)

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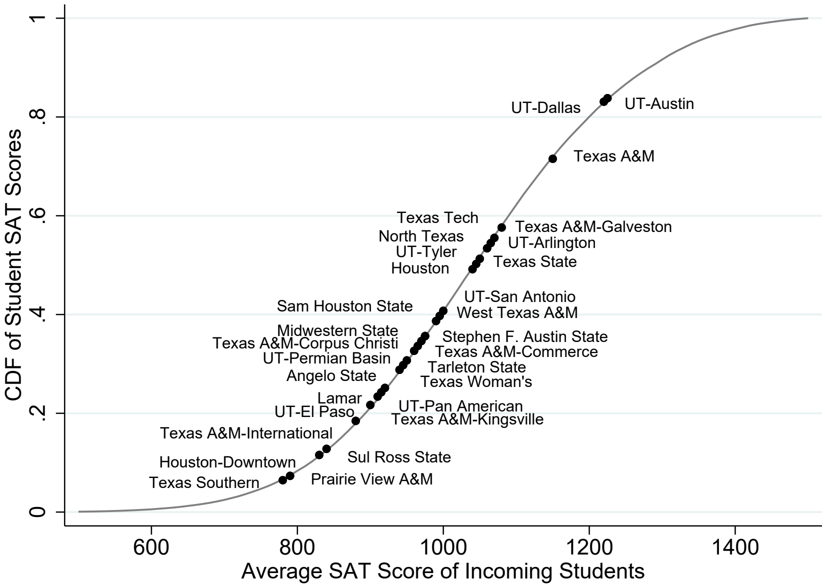
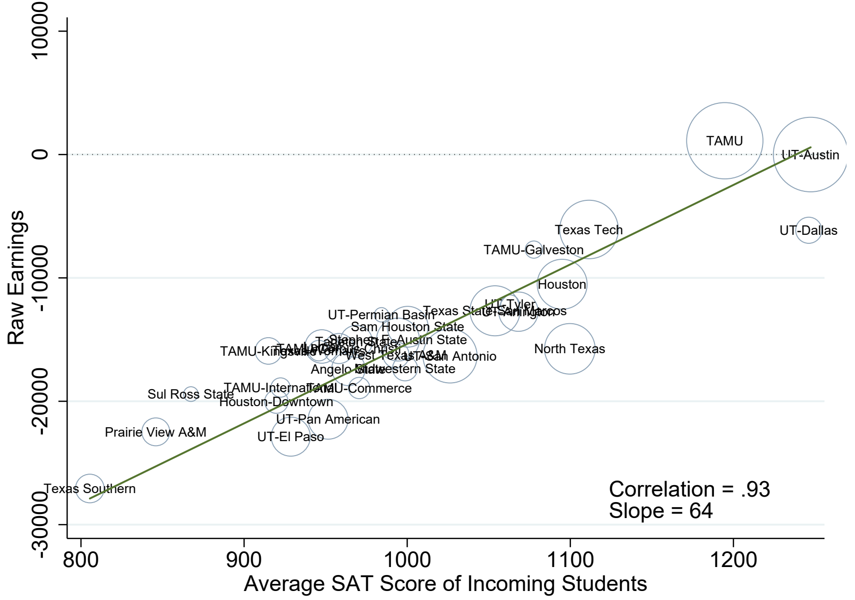
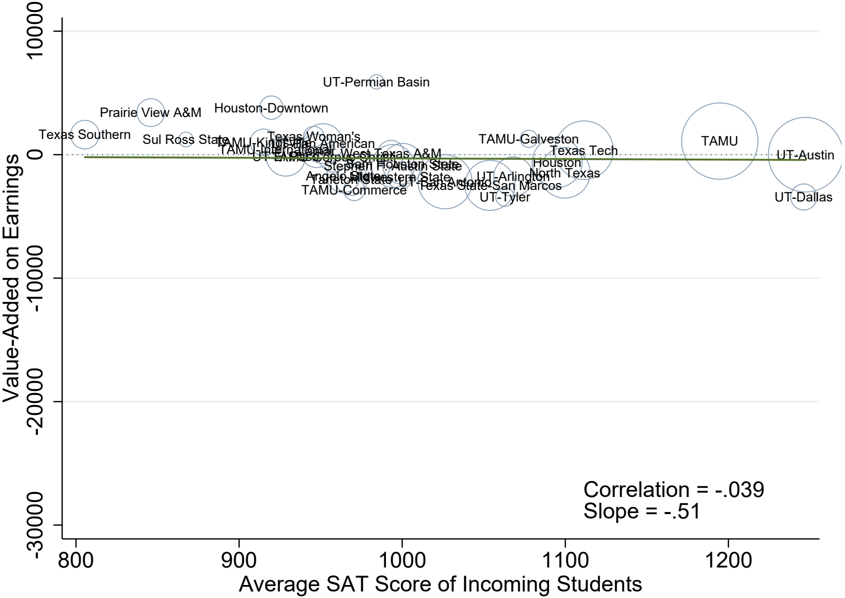
Reminder: Selectivity Distribution



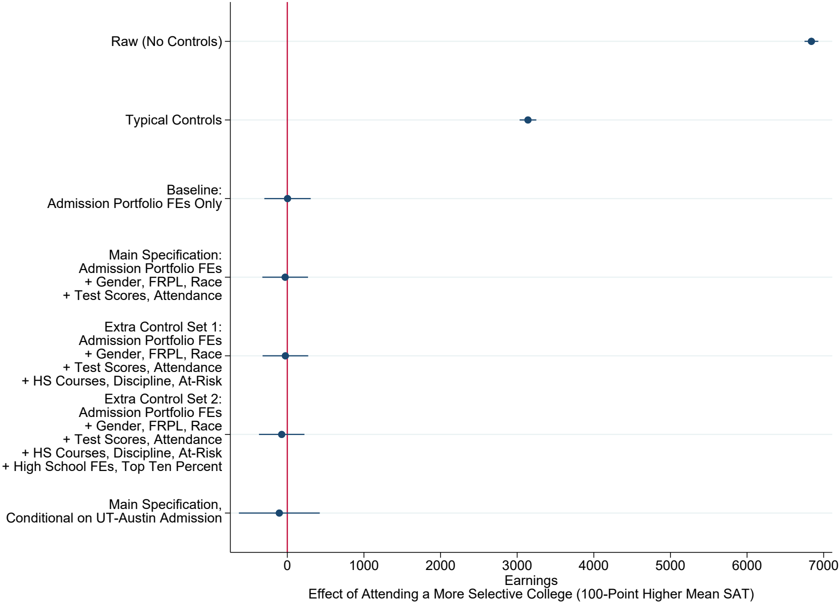
Selectivity: Strong Predictor of Raw Earnings



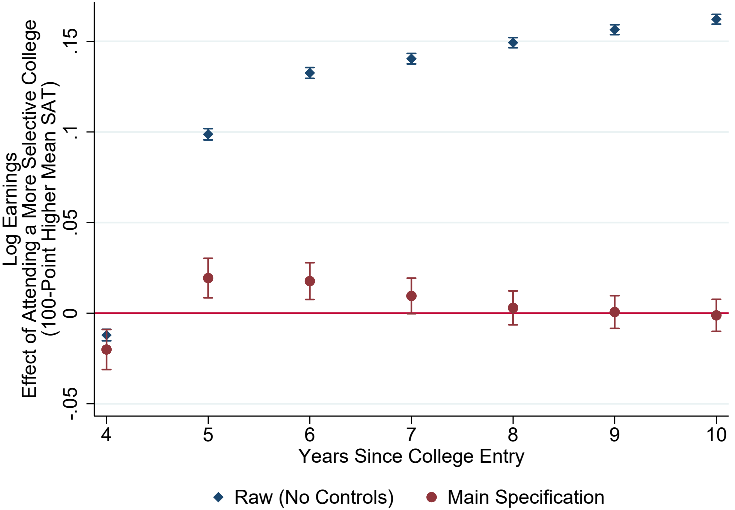
Selectivity: Uninformative about Earnings Value-Added



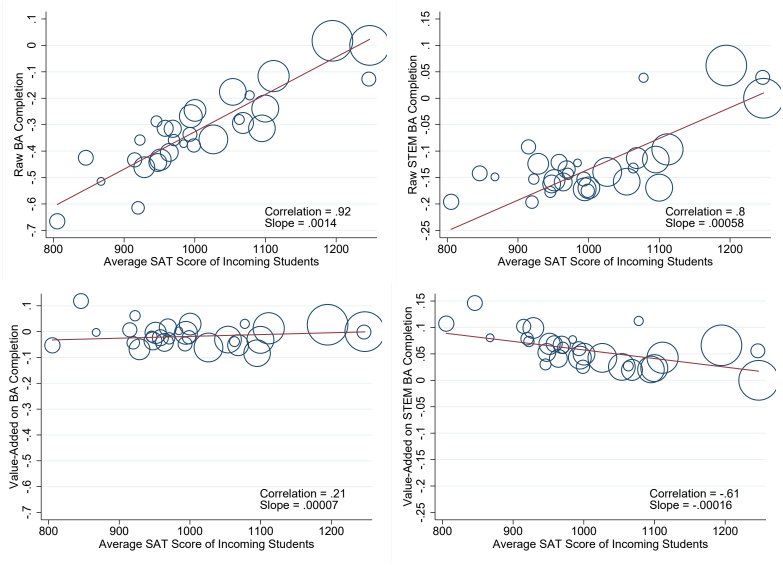
Selectivity: Student-Level Regressions (Replicating DK)



Selectivity: Early Career Dynamics (Employer Learning?)



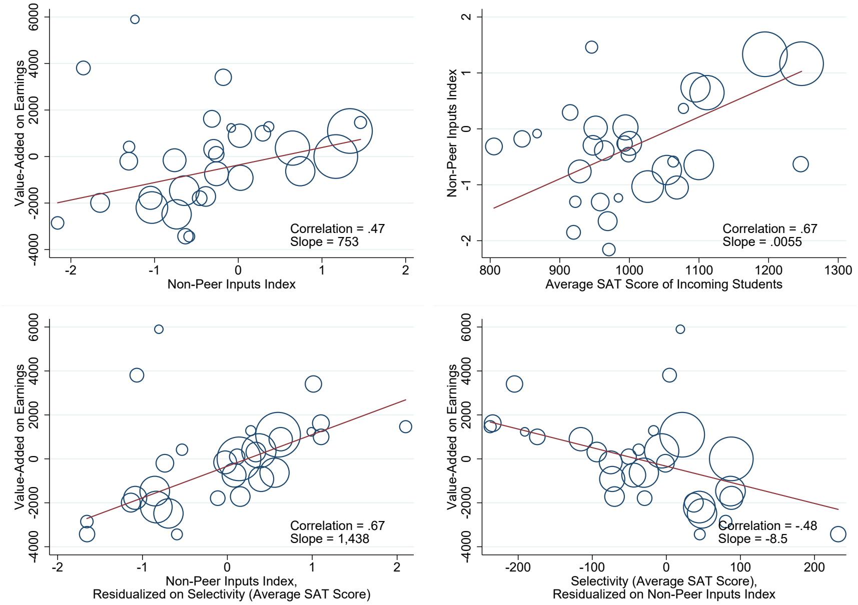
Selectivity: BA Completion & STEM Majors



Beyond Selectivity: Non-Peer College Inputs

	BA Completion	Earnings
Non-Peer College Inputs: Correlation with Causal Value-Added		
Instructional expenditures per student	.342	.317
Academic support expenditures per student	.158	.288
Student services expenditures per student	.295	.076
Share of faculty who are full-time	.371	.450
Share of faculty who are tenured or on tenure-track	.267	.411
Average faculty salary	.082	.090
Faculty/student ratio	.433	.433
Share of degrees in STEM fields	.332	.422

Peer vs. Non-Peer Inputs



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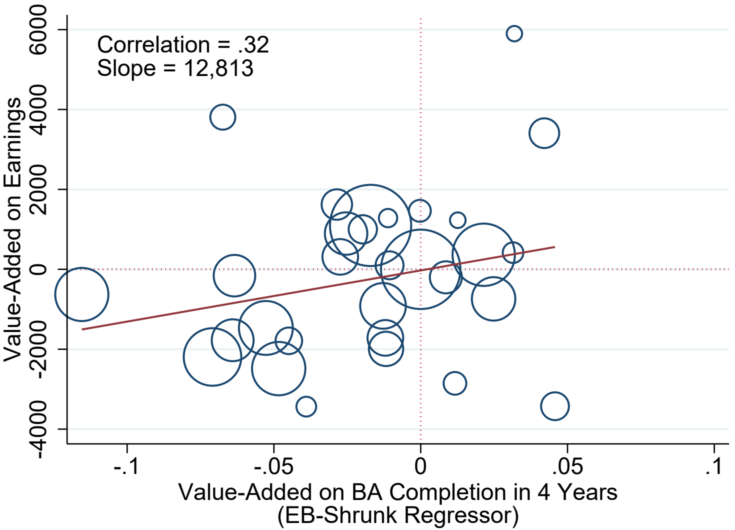
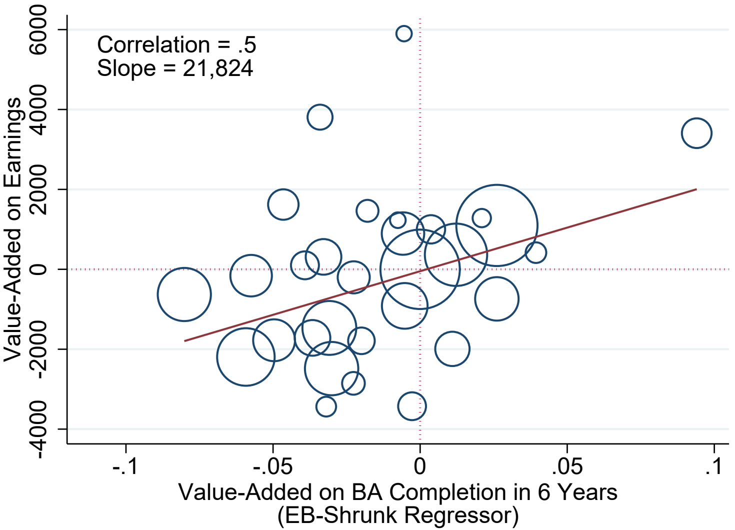
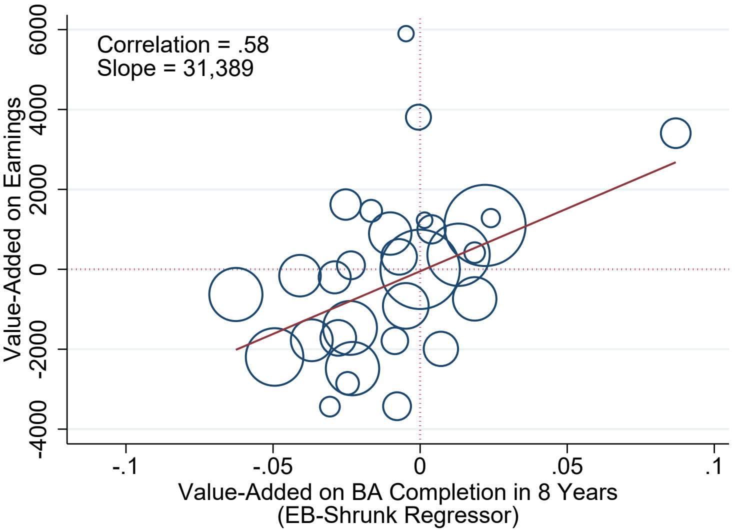
VA on Earnings vs. VA on BA Completion: in 4 Years



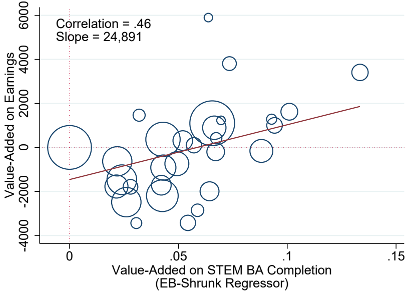
VA on Earnings vs. VA on BA Completion: in 6 Years

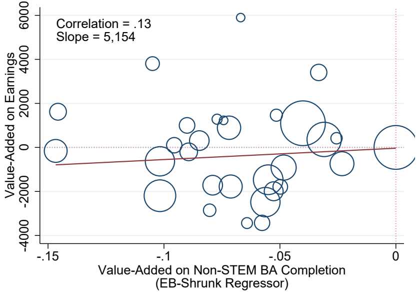


VA on Earnings vs. VA on BA Completion: in 8 Years



VA on Earnings vs. VA on STEM and Non-STEM Degrees





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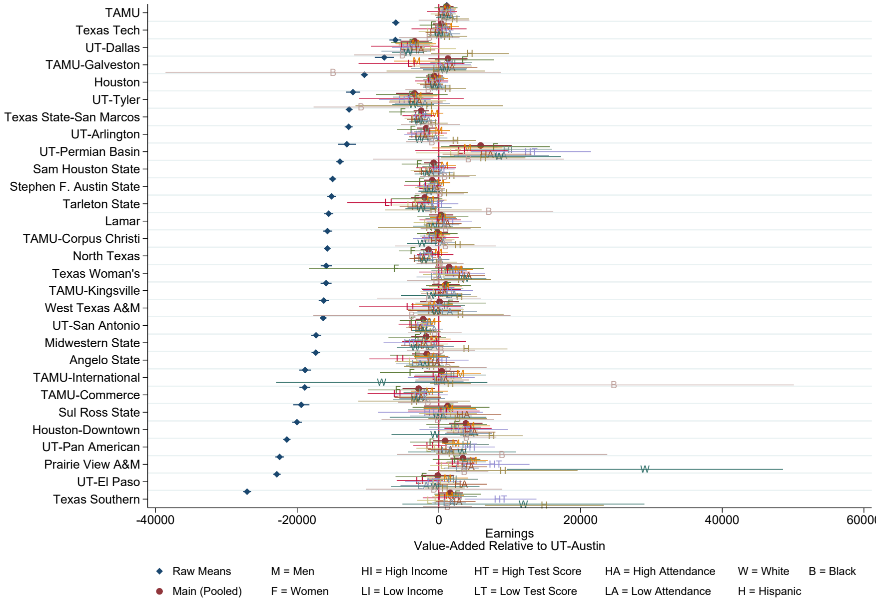
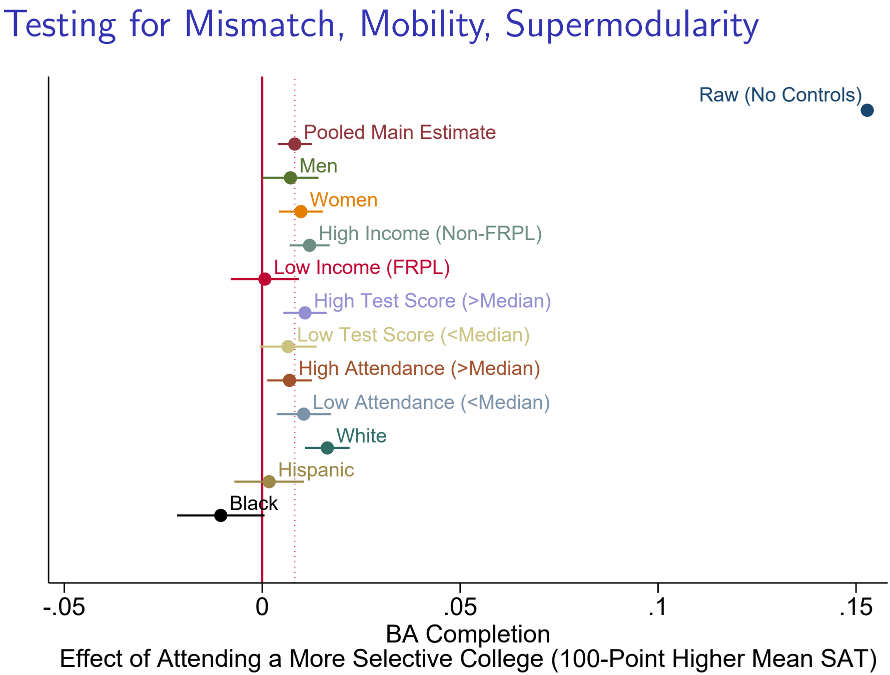
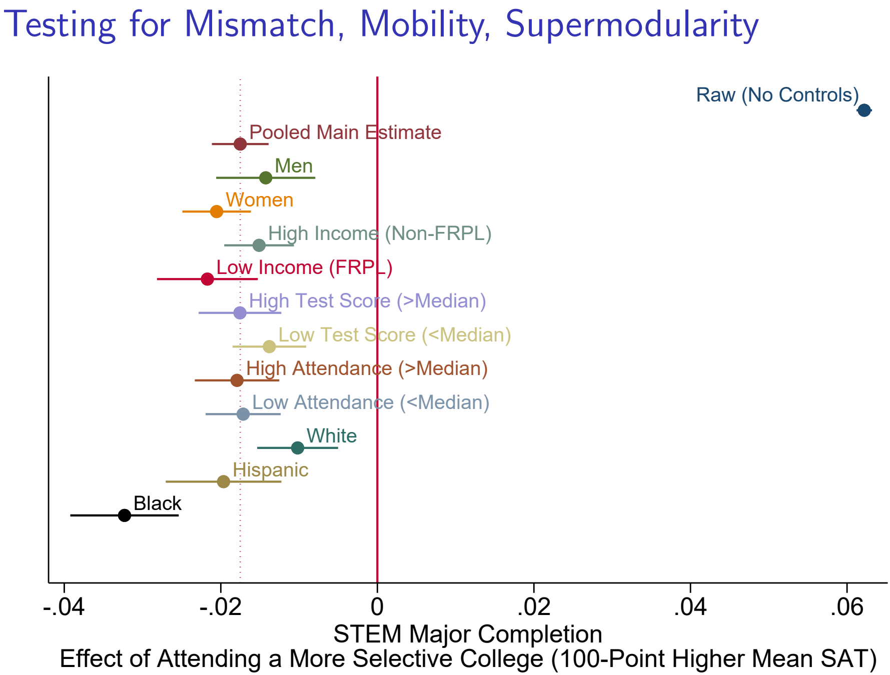
VA Estimates by Subpopulation: Earnings

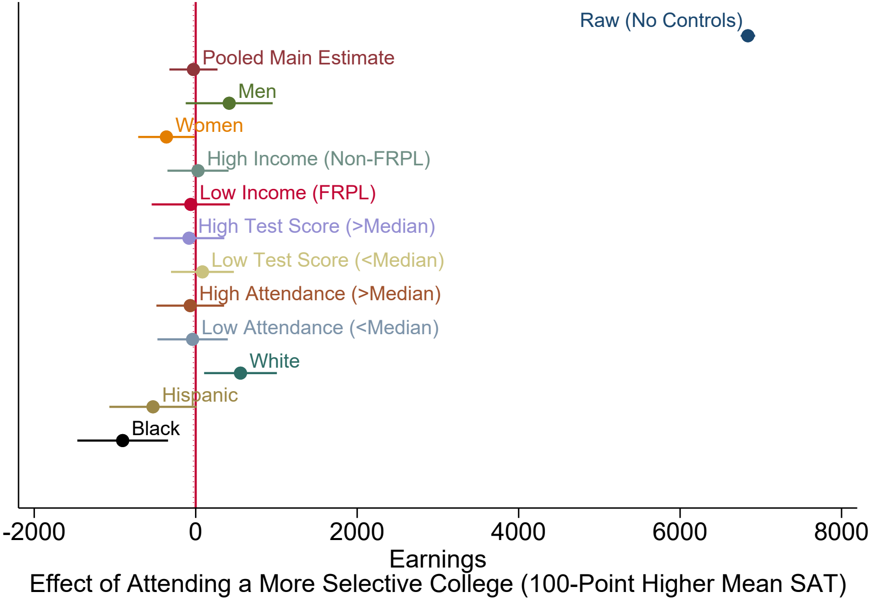



Testing for Mismatch, Mobility, Supermodularity
Raw (No Controls)
Pooled Main Estimate
Men
Women
High Income (Non-FRPL)
Low Income (FRPL)
High Test Score (>Median)
Low Test Score (<Median)
High Attendance (>Median)
Low Attendance (<Median)
White
Hispanic
Black
-.05
0
.05
.1
.15
BA Completion
Effect of Attending a More Selective College (100-Point Higher Mean SAT)

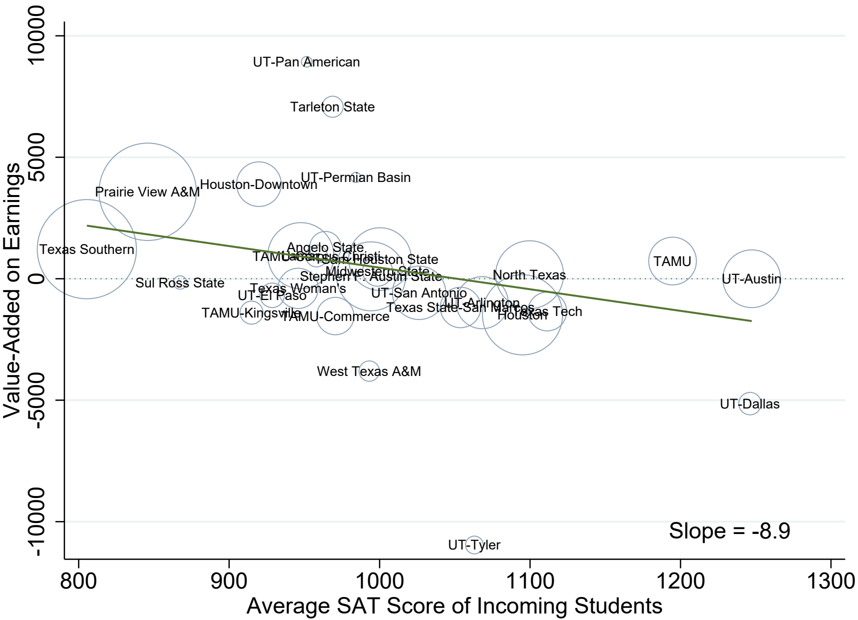


Testing for Mismatch, Mobility, Supermodularity
Raw (No Controls)
Pooled Main Estimate
Men
Women
High Income (Non-FRPL)
Low Income (FRPL)
High Test Score (>Median)
Low Test Score (<Median)
High Attendance (>Median)
Low Attendance (<Median)
White
Hispanic
Black
-.04
-.02
0
.02
.04
.06
STEM Major Completion
Effect of Attending a More Selective College (100-Point Higher Mean SAT)

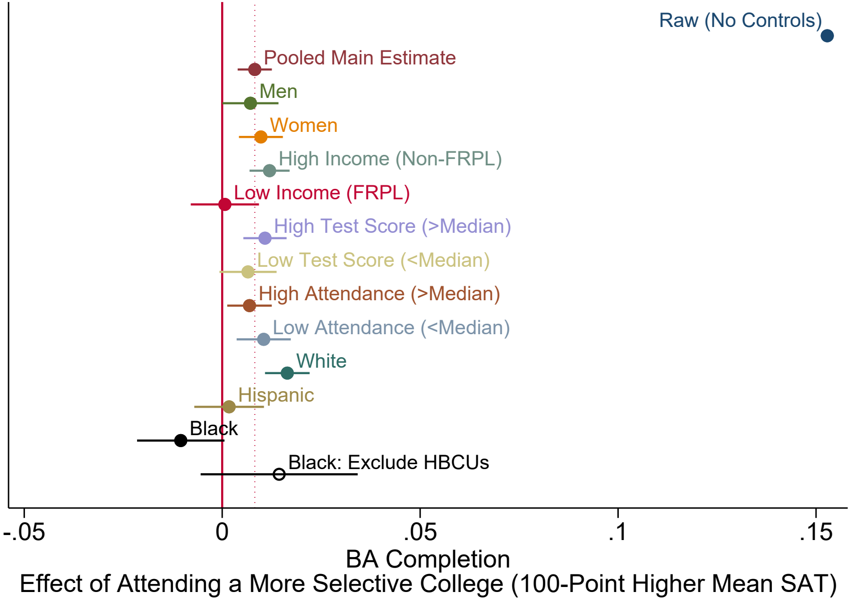
Testing for Mismatch, Mobility, Supermodularity



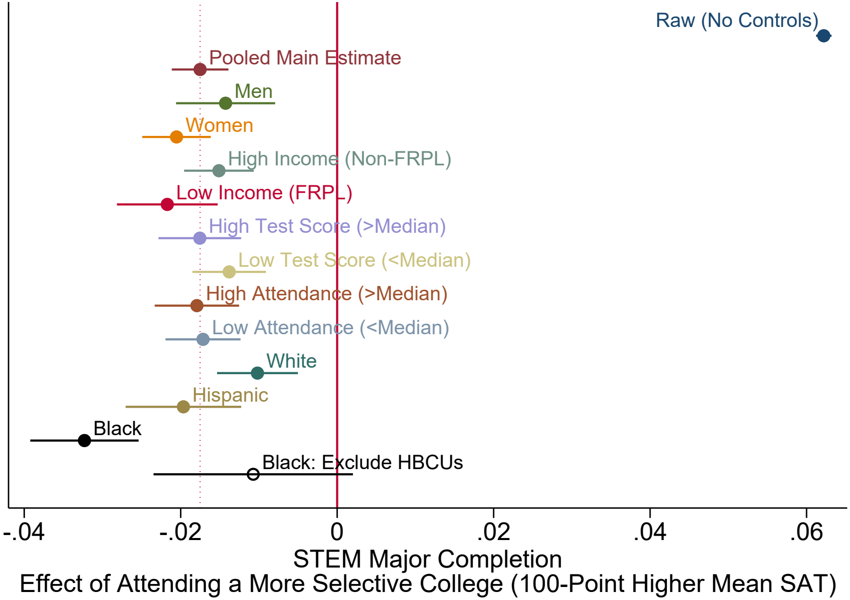
Black Subsample: The Role of HBCUs



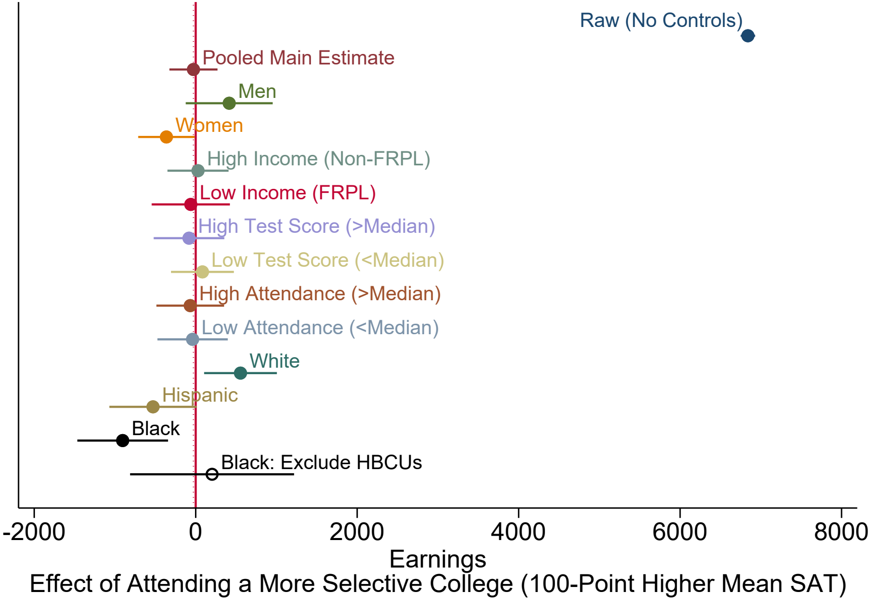
Testing for Mismatch: Across the Non-HBCUs



Testing for Mismatch: Across the Non-HBCUs



Testing for Mismatch: Across the Non-HBCUs



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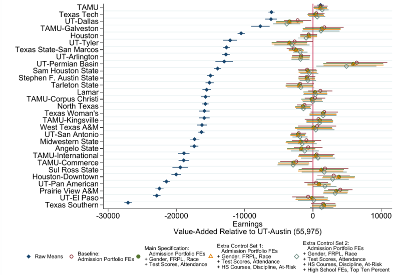
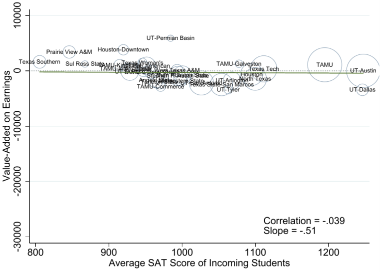
Conclusion

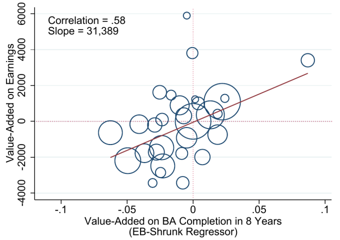
Validating the Matched Applicant Approach: OVB



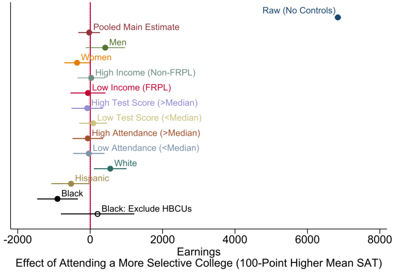
Selectivity: Uninformative about Earnings Value-Added



VA on Earnings vs. VA on BA Completion: in 8 Years

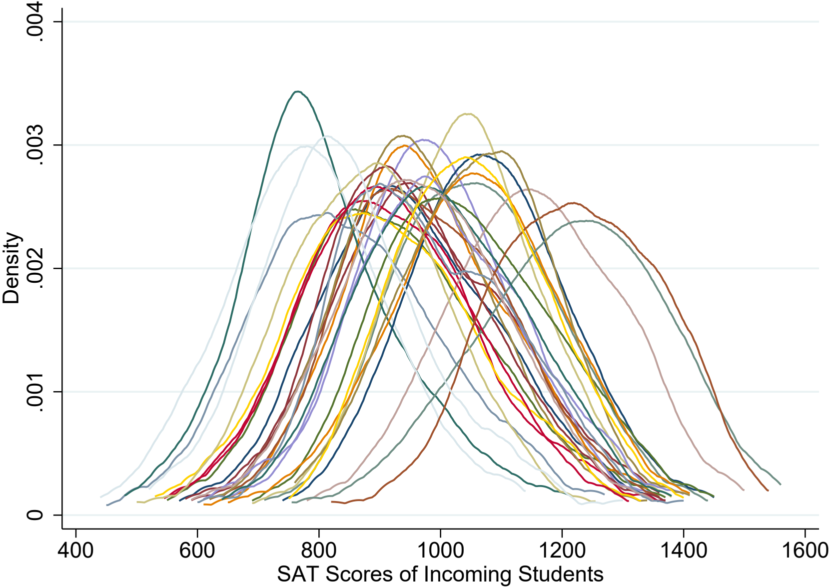


Testing for Mismatch, Mobility, Supermodularity

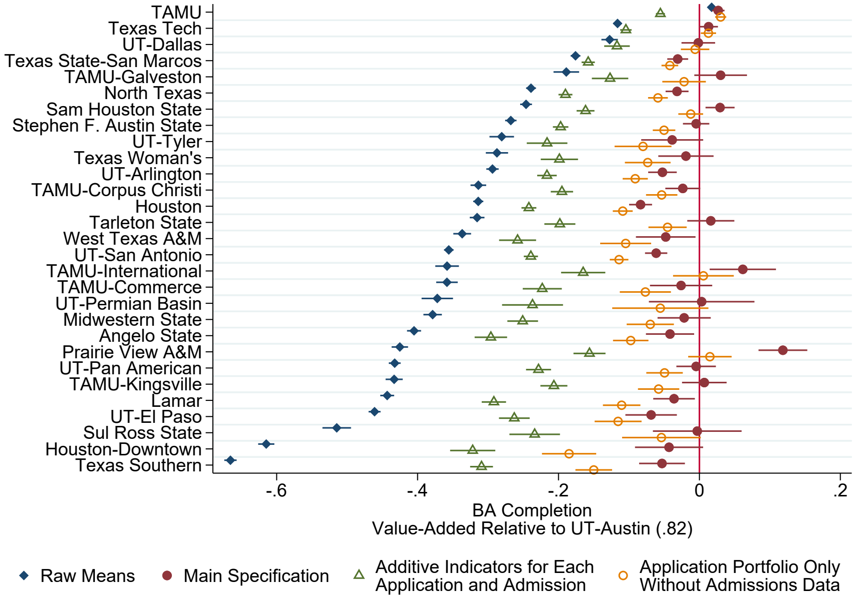


Appendix

Data: Variation Within (75%) vs. Across (25%) Schools



Insufficiency of Simpler Portfolio Specifications



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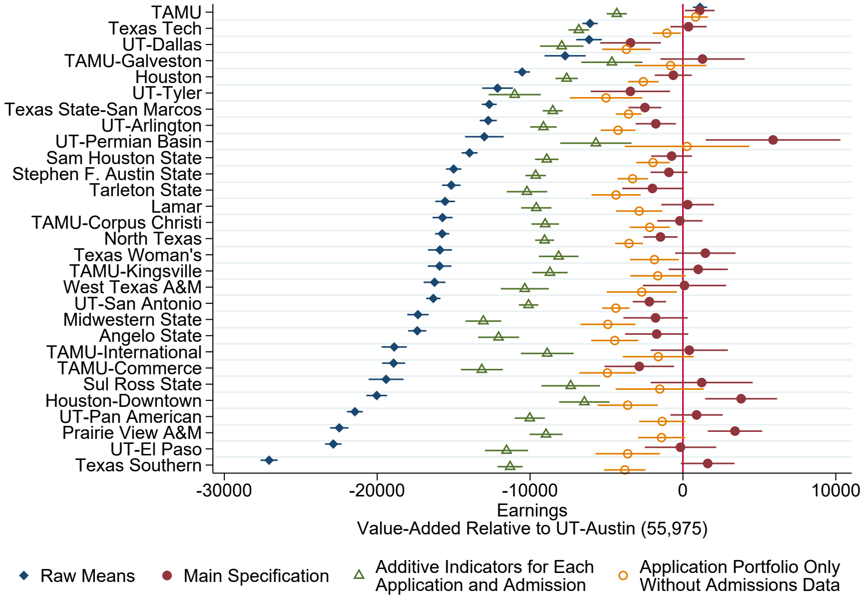
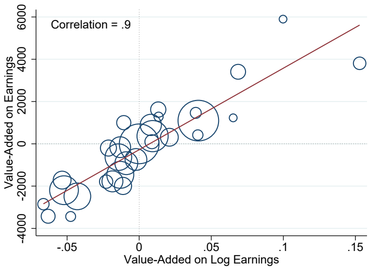
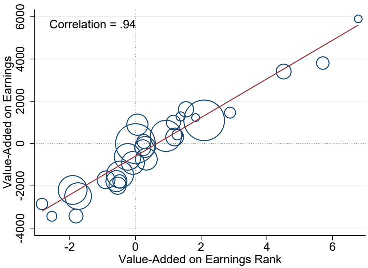
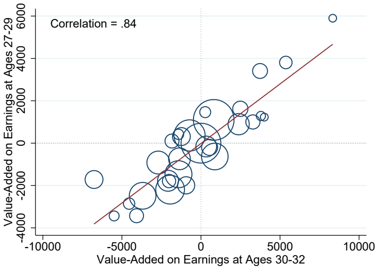


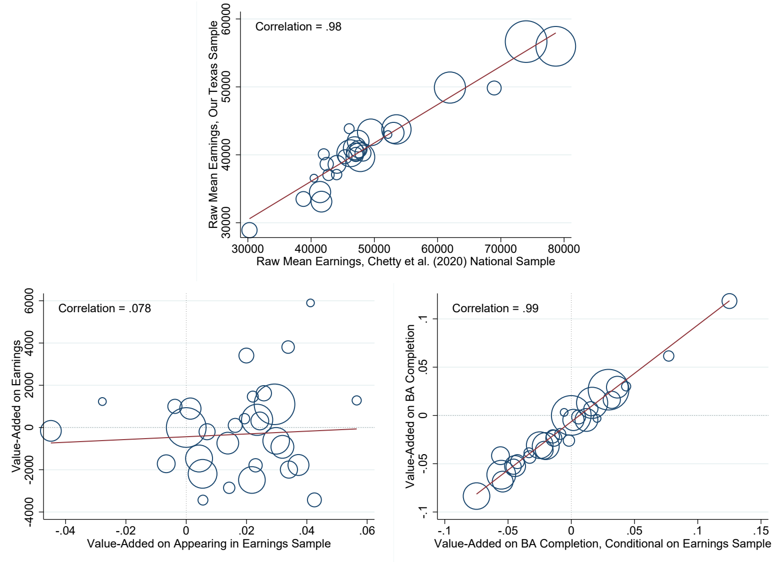
Additional Checks: Earnings Measurement



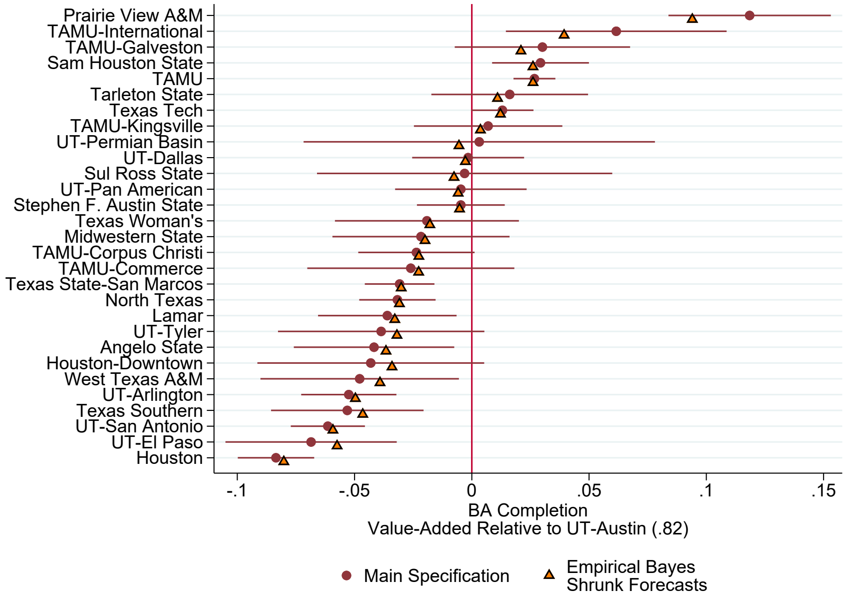




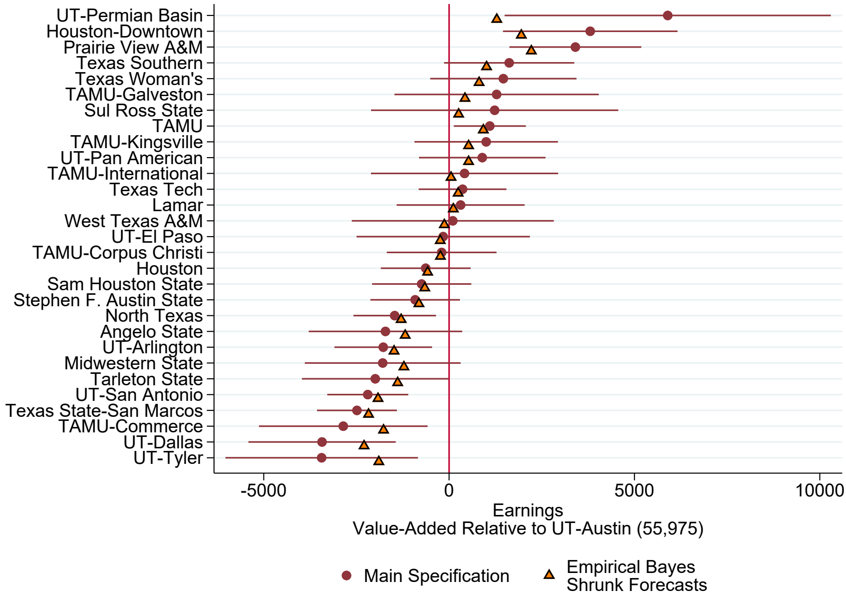
Additional Checks: Missing Earnings



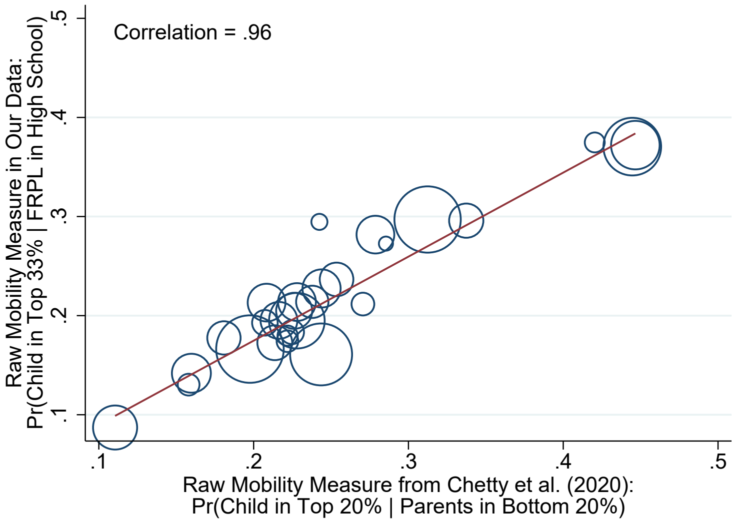
Accounting for Estimation Error: EB Shrunk Forecasts



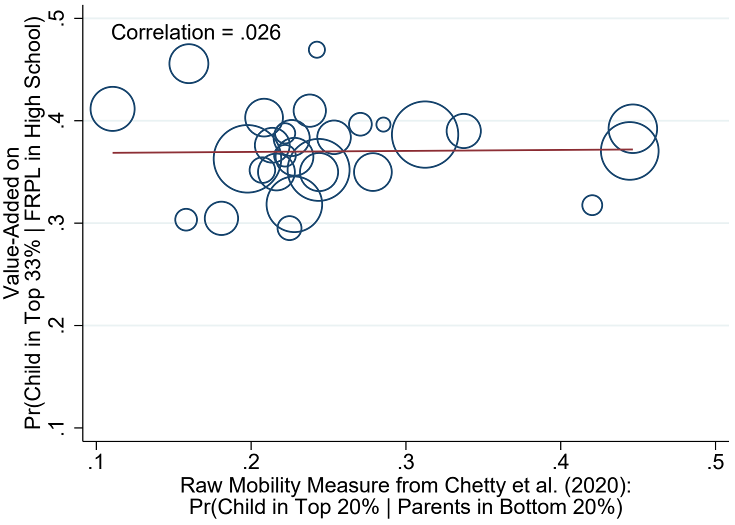
Accounting for Estimation Error: EB Shrunk Forecasts



Intergenerational Mobility Statistics: Our Raw Analogue



Intergenerational Mobility Statistics vs. Causal VA



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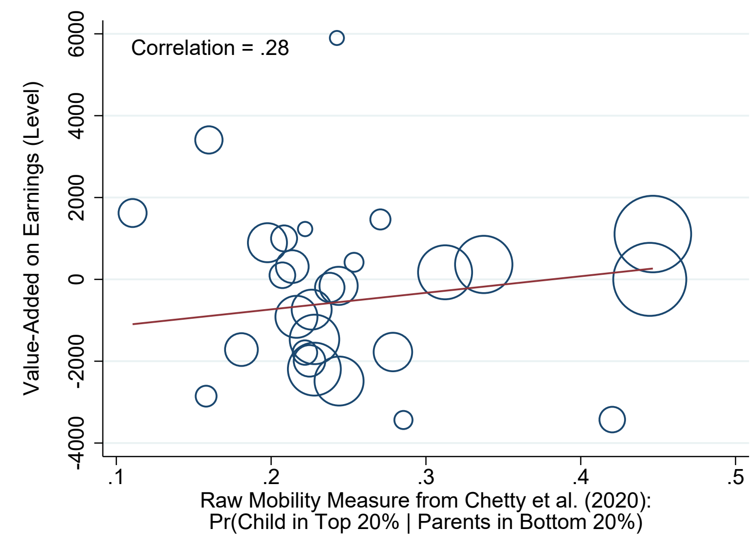
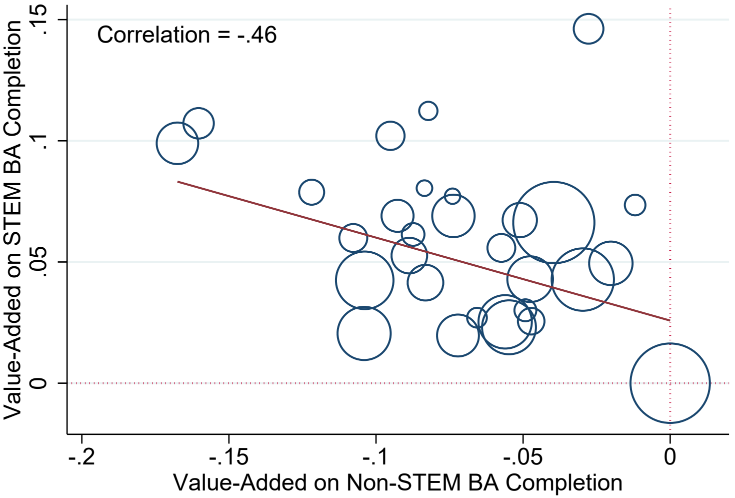
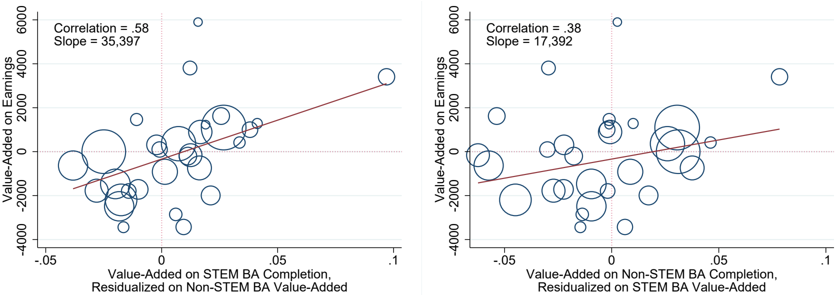


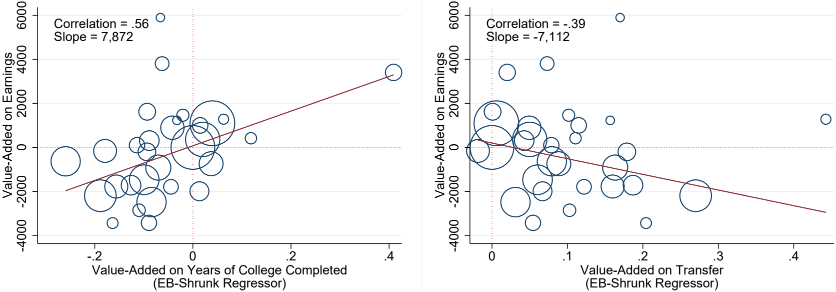
STEM VA vs. Non-STEM VA



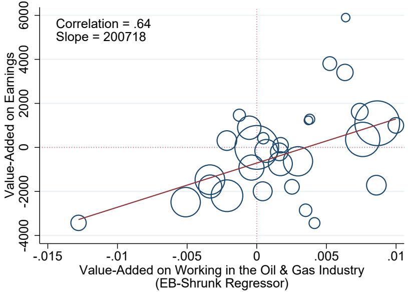
STEM and Non-STEM: Residualized on Each Other

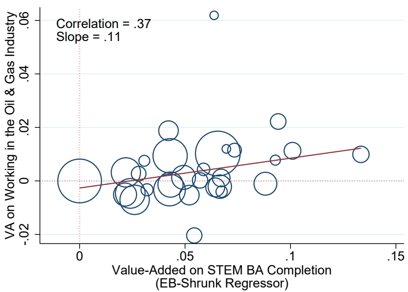


Other Potential Mechanisms: Persistence and Transfer

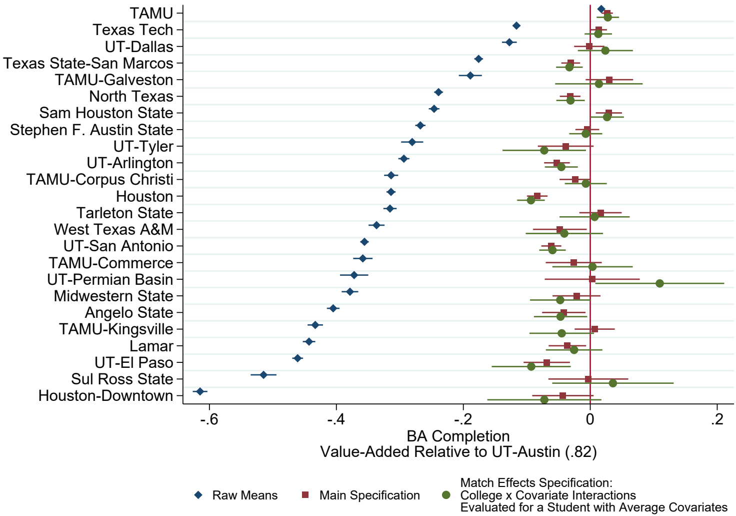


Other Potential Mechanisms: Industry of Employment





Allowing Match Effects: Similar VA for Average Student



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