The Effect of Student Debt on Entrepreneurship: Evidence from Online Social Networks

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AEA session on Financing Entrepreneurship and Innovation

Motivation

Student debt has increase dramatically

- Student debt increased more than fivefold over the past 15 years
- \$260 billion in 2004 → \$1.46 trillion in 2019 (NYFED, 2018)
- Intense political debate (Biden, Sanders, Warren etc.)
- Proposals vary from universal "free college" to targeted need-based reforms

What are the long-term effects on labor outcomes?

- Most papers study *immediate effects*: Student debt ↑ ⇒ consumption ↓ (Cooper and Wang 2014, Mezza et al. 2016, Di Maggio et al. 2020, Mueller and Yanellis 2020)
- What is the *long-term* effect on labor market incentives and career trajectories?

Does student debt effect risk taking in labor markets?

- Firm creation down almost half since 1990 (US Census, Decker et al. 2015)
- Significant decrease in entrepreneurship and self-employment among the 20-34 year olds Entrepreneurs by Age

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What is the effect of student debt on job outcomes?

The evidence has been mixed and inconsistent

- Some studies find that student debt is associated with **higher wages**
  Minicozzi (2005); Rothstein and Rouse (2011); Chapman (2016); Daniels and Smythe (2019); Denning et al. (2019)
- Some have found it to be associated with **lower wages**
  Weidner (2016); Gervais and Ziebarth (2017); Maggio et al. (2019); Bettinger et al. (2019); Scott-Clayton and Zafar (2019)
- Others have found **no effect on wages**
  Goodman, Isen and Yannelis (2020)

This range in estimates is often attributed to empirical challenges

- Surveys with few observations (e.g. SCF, BBS, NLSY97)
- Study one-off policy changes or restrict sample to low-income or low-credit-score individuals

This Paper

Research Question

- How does student debt affect *initial* choices and *long-term* career trajectories?

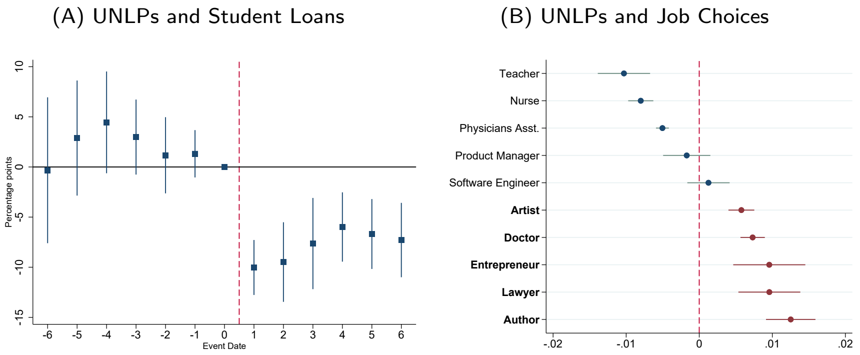
Empirical design

- Resume data from an professional networking database, merged with university records and commencement programs
- Staggered implementation of “Universal No Loan Policies” (UNLPs) from 1998-2018
- Substantial effect: $\Delta \text{Pr}\{\text{student debt}\} > 1/3$

Results

- **Main finding:** Student debt can lead students to choose occupations that have both high and low earnings at different point of their careers
- Student debt $\downarrow \Rightarrow$ choosing occupations associated with lower **initial wages**, higher **compensation slope**, and generally lower **job security**
- Highlights the importance of **life-cycle dynamics**

Preview of Results



Note: This figure plots the regression coefficients and 95% confidence interval for regressions of the probability of a specific job on year-dummies relative to the implementation of the UNLP. Panel A reports the regression coefficients of students taking a student loan on year-dummies relative to the implementation of the UNLP, and Panel B the probability of having a different types of occupations job where the outcome variables are measured within five years after graduation, and the regression includes school and cohort fixed effects. The data sources are IPEDS and a large professional networking database.

Outline

1. Theoretical Framework
2. Data
3. Empirical Design
4. Results
5. Conclusion

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1. **Theoretical Framework**
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Theoretical Framework

Two-period benchmark model

$t = 0 \sim$ first 5 years after college, $t = 1 \sim$ the following 10-15 years, $d \sim$ student debt

$$\max_{j, a_1} \ln(c_0) + \ln(c_1) \quad \text{s.t.} \quad a_1 = (y_0 - c_0 + a_0 - d - j\theta) \quad \text{and} \quad a_1 \geq 0$$

- Period 0: Choose job $j \in \{0, 1\}$ and savings a_1; and pay investment cost $j\theta$

  $j = 0 \sim$ office job (low earnings growth), $j = 1 \sim$ entrepreneur (high earnings growth, investment cost θ)

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- Period 1: Receive job-dependent wages w_0 or w_1
  Investment cost corresponds to start-up costs and additional training: $w_0 < w_1$

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Solution

- Choose to invest θ to get the high-growth job, $j = 1$, if and only if:

$$\theta < \left(\frac{w_1 - w_0}{w_1} \right) (y_0 - d)$$

Theoretical Framework

Two-period benchmark model

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$$\theta < \left(\frac{w_1 - w_0}{w_1}\right)(y_0 - d)$$

Empirical Hypothesis

- Higher student debt, d, increases the probability of a job with a flat earnings path

$$\frac{\partial j}{\partial d} < 0$$

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1. Theoretical Framework
2. **Data**
3. Empirical Design
4. Results
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Data

Employment data

- Large professional network database (hand collected)
- Includes: education, job type, employer, location, dates, job skills
- Self-reported

University records

- Integrated Postsecondary Education Data System (IPEDS)
- Commencement programs and yearbooks (hand collected)

Sample representation

- Selective "elite" universities (Northwestern, Stanford, and Princeton)
- Liberal-arts colleges (Amherst College, College of the Ozarks, Haverford College)
- Preliminary match-rate with commencement programs: $> 85\%$

Outline

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Institutional Background

Four types of Loan Reduction Policies

- No-loan policies, loan caps, no parental contributions, and workstudy programs
- 85 schools adopted at least one of the policies between 1998-2018

Focus for today's talk: Universal No-Loan Policies (UNLPs)

- 55 schools have adopted a no-loan policy (21 for all students) Implementation timeline
- Some schools have reversed the policy later on

UNLP algorithm

$$\underbrace{\text{COA}}_{\text{Cost of Attendance}} - \underbrace{\text{EFC}}_{\text{Effective Family Contribution}} = \underbrace{\text{FinAid}}_{\text{Financial Aid}} + \underbrace{\cancel{\text{SD}}}_{\text{Student Debt}}$$

Empirical Design

Theoretical framework

- Jobs vary across: (1) expected earnings, (2) job security, and (3) compensation slope
- Ex. 1: English major trading off expected earnings vs. job security:

  "*Teaching in High School*" vs. "*Freelance writer and author*"
- Ex. 2: Biology major trading off expected earnings vs. compensation slope:

  "*Physician*" vs. "*Nurse*"
- Ex. 3: Economics major trading off expected earnings vs. job security:

  "*App Start-Up*" vs. "*Work in a bank*"

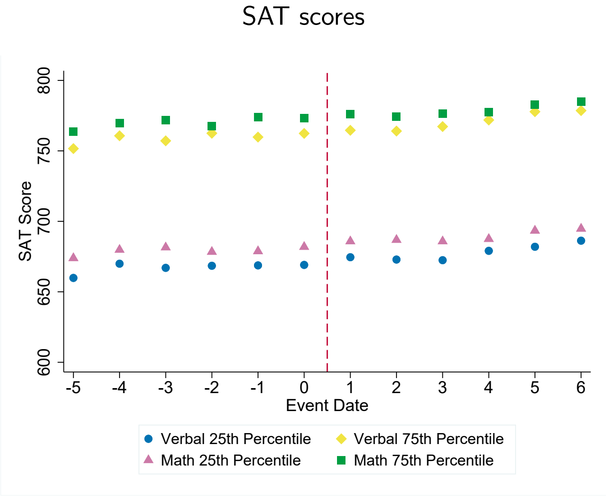
Empirical tests

- **Event-study:**
  $LaborOutcome_{ist\to\tau} = \sum_{j=-6}^{6} \beta_j EventYearDummies_j + \gamma_s + \gamma_t + \epsilon_{sjt}$
- **DID:** $LaborOutcome_{ist\to\tau} = \alpha + \beta\{\text{Policy}_s \times \text{Post}_t\} + \gamma_s + \gamma_t + \epsilon_{ist}$

  (individual i, school s, graduating cohort t, event-date j, years after graduation τ)

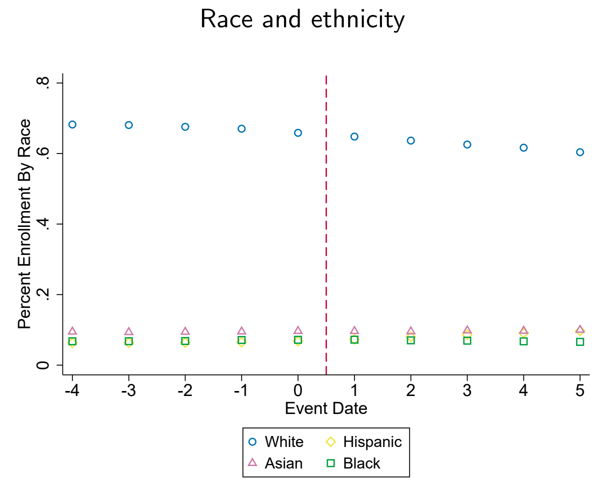
Empirical Concern: Selection bias

Composition of Students Does Not Change: SAT



Note: This figure plots the averages of the 25th and 75th percentiles of SAT scores relative to year that an institution implemented a UNLP. The data source is Integrated Postsecondary Education Data System (IPEDS).

Composition of Students Does Not Change: Race



Note: This figure plots the average of the percent of White, Black, Asian, and Hispanic students across institutions that implemented a UNLP relative to the event year. The data source is the Integrated Postsecondary Education Data System (IPEDS).

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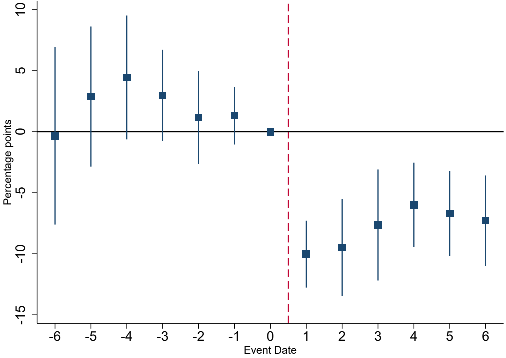
Effect of No-Loan Policy

$$LaborOutcome_{ist\rightarrow\tau} = \sum_{j=-6}^{6} \beta_j EventYearDummies_j + \gamma_s + \gamma_t + \epsilon_{sjt}$$

Undergraduates with Student Loans



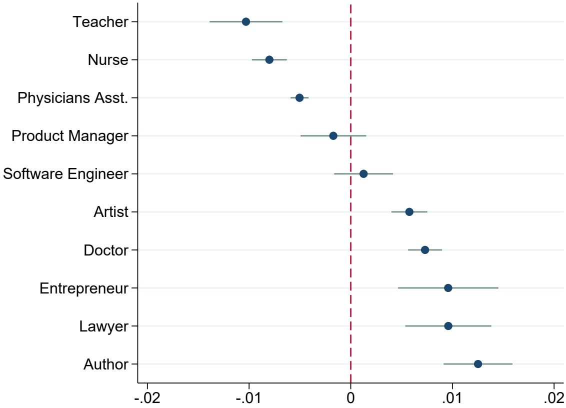
Note: This figure plots the regression coefficients and 95% confidence interval for regressions of the percent of students taking a student loan on year-dummies relative to the implementation of a UNLP. Data source: IPEDS. Raw averages

- Preliminary evidence shows largest benefits for student's from the middle class Compliers

Effect of NLP on Job Types: DID

$$LaborOutcome_{ist\to\tau} = \alpha + \beta\{\text{Policy}_s \times \text{Post}_t\} + \gamma_s + \gamma_t + \epsilon_{ist}$$

Effect of No-Loan Policy on Job Types



Note: This figure plots the regression coefficients and 95% confidence interval for difference-in-differences regressions of job types on NLP treatment. Each row plots the coefficient for the interaction term between an NLP school and Post-NLP implementation. The outcome variables are indicator functions measured within the first five years after graduation.

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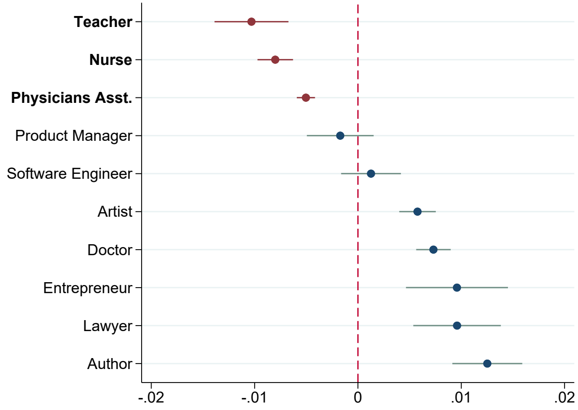

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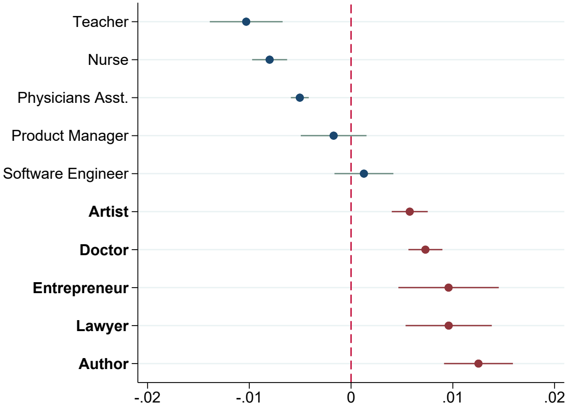

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Regression table: DID

DID Estimates (Panel A)

	(1) Teacher	(2) Nurse	(3) Physicians Asst.	(4) Product Manager	(5) Software Engineer
UNLP $\times$ *Post*	-1.03***	-0.80***	-0.50***	-0.17	0.13
	(0.17)	(0.081)	(0.042)	(0.15)	(0.14)
Constant	4.48***	0.90***	0.66***	2.09***	2.84***
	(0.24)	(0.21)	(0.048)	(0.34)	(0.29)
Year and cohort FE	✓	✓	✓	✓	✓
N	53,012	53,012	53,012	53,012	53,012

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

DID Estimates (Panel B)

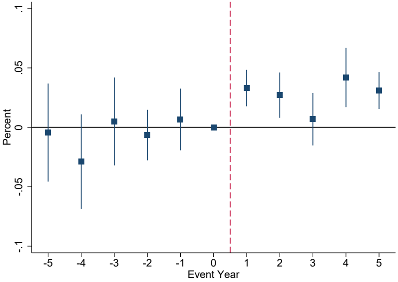
	(1) Artist	(2) Author	(3) Doctor	(4) Entrepreneur	(5) Lawyer
UNLP $\times$ *Post*	0.58***	1.25***	0.73***	0.96***	0.96***
	(0.083)	(0.16)	(0.079)	(0.23)	(0.20)
Constant	-0.30	1.83***	0.17	3.94***	0.92**
	(0.15)	(0.33)	(0.13)	(0.21)	(0.25)
Year and cohort FE	✓	✓	✓	✓	✓
N	53,012	53,012	53,012	53,012	53,012

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

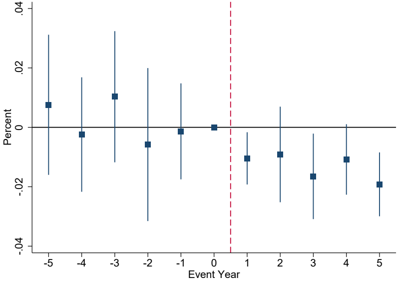
Effect of NLP on Job Types: Event-Study

$$LaborOutcome_{ist \to \tau} = \sum_{j=-6}^{6} \beta_j EventYearDummies_j + \gamma_s + \gamma_t + \epsilon_{sjt}$$

(A) Creative/self-employed jobs



(B) Teaching



Note: This figure plots the regression coefficients and 95% confidence interval for regressions of the probability of a specific job on year-dummies relative to the implementation of the UNLP. Panel A reports the probability of having a creative job as an Artist or an Author/Writer, and Panel B the probability of having a Teaching job. The outcome variables are measured within the first five years after graduation, and the regression includes school and year fixed effects. The data source is a large professional networking database.

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Conclusion

Research Question

- How does student debt affect *initial* job choices and *long-term* career trajectories?

Empirical design

- University records merged with online resume data
- Staggered implementation of "Universal No Loan Policies" (UNLPs) from 1998-2018

Results

- Student debt simultaneously leads to both higher and lower earnings
- Student debt $\downarrow \Rightarrow$ jobs that generally have lower **initial wages**, higher **compensation slope**, and lower **job security**

Going Forward

- Aggregate all occupations at the 6-digit SOC code level
- Discipline the categorization of high and low earnings slope occupations

THANK YOU

Feedback and comments are much appreciated:

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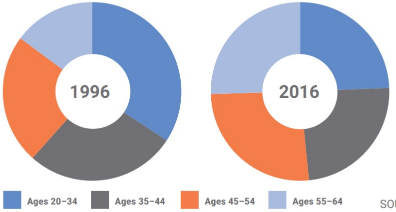
New Entrepreneurs by Age

Changes in Composition of New Entrepreneurs by Age (1996, 2016)



Age	1996	2016
Ages 20–34	34.27%	24.37%
Ages 35–44	27.36%	24.04%
Ages 45–54	23.55%	26.13%
Ages 55–64	14.83%	25.46%

SOURCE: Kauffman Foundation calculations from CPS.

Kauffman Foundation

Expected Benefit NLP

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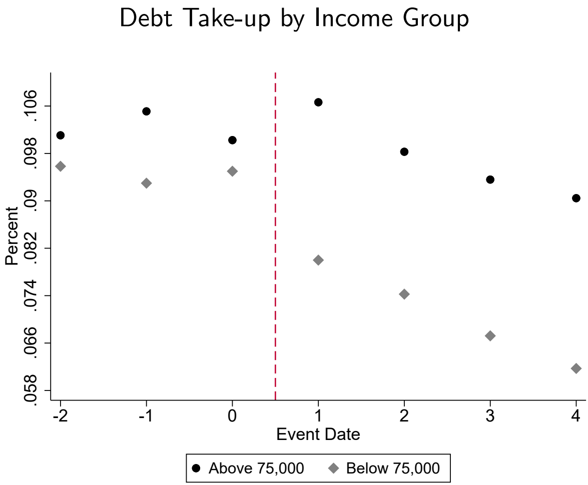
- Hypothesize that middle-class students will see the largest benefits



This figure plots the fraction of students with student debt of the total student population by household income level for every year relative to the implementation of a no-loan policy. The data source is College Scorecard.

Implementation of No Loan Policies - Treatment Intensity

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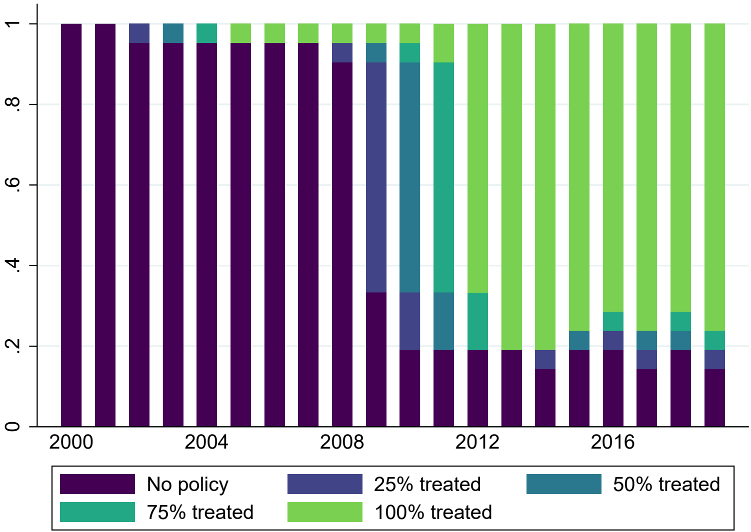

Fraction of Students with Debt (raw average)

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