Non-College Occupations, Workplace Automation, and the College Gender Gap

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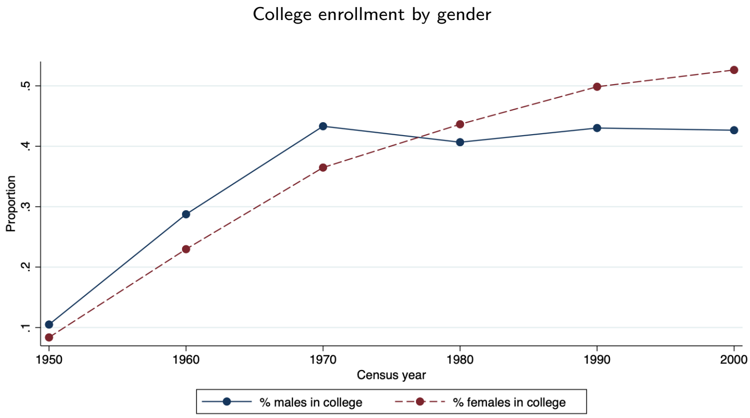
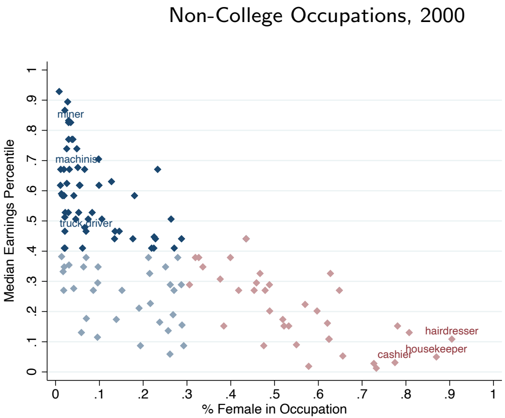
Women overtook men in college enrollment



Source: IPUMS decadal census data for 1950-2000; American Community Survey yearly data for 2001-2010. 18-30 year olds.

- Open question: Why do women exceed men in college-going?
  - When men earn and work more than women
- Marriage market premium (Chiappori, Iyigun, Weiss, 2009; Chiappori, Salanie, Weiss, 2017; Low, 2019; Zhang, 2021; Ge, Isaac, Miller, 2022)
- Most of the literature focuses on gender differences in the ability to prepare for college (supply side)
  - Academic performance (Goldin, Katz, and Kuziemko, 2006; Becker, Hubbard, and Murphy, 2010); non-cognitive abilities (Bertrand and Pan, 2013)
- In contrast, this paper explores gender differences in non-college job prospects (demand side)
  - Among high school graduates, women face worse job options than men

“Missing quadrant” of high-paying female non-college occs



- Traditionally “male” occupations can pay highly
- Occupations which employed women have significantly lower median earnings

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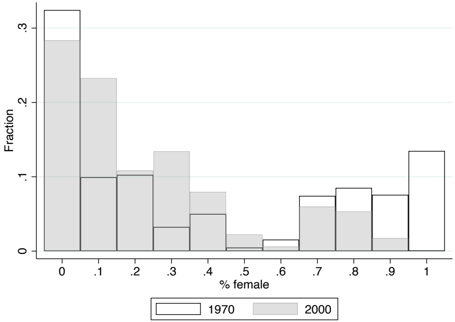
Decline in women's non-college occupations over time



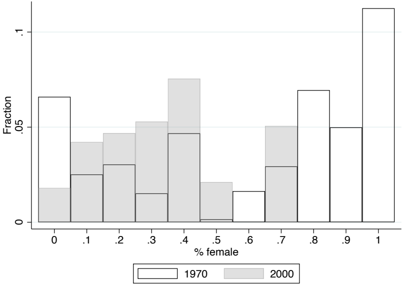
Source: IPUMS decadal census microdata (1970) and ACS data (2010). 18-30 year olds.

- In 1970, 70% of non-college working women held "routine" occupations
  - secretary, stenographer, clerical worker, telephone operator, typist
- 66% decline in share of secretarial jobs, 95% decline in share of typist jobs from 1970 to 2000

College Occupations | Occupations by Education, Model

Decline in women's non-college occupations – driven by routine occs

(a) Routine Occupations



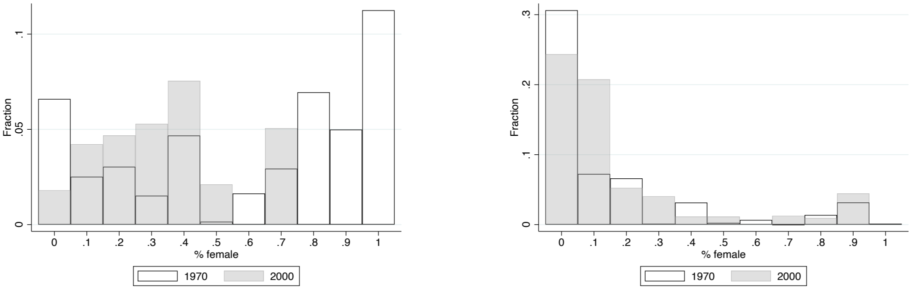
- 1970: among high routine occupations, most were female-dominated
- By 2000: no more high routine female-dominated occupations

College occupations

Decline in women's non-college occupations – driven by routine occs

(a) Routine Occupations

(b) Non-routine Occupations



- 1970: among high routine occupations, most were female-dominated
- By 2000: no more high routine female-dominated occupations
- Non-routine occupations: little change over time

College occupations

Decline in women's non-college occupations – driven by routine occs

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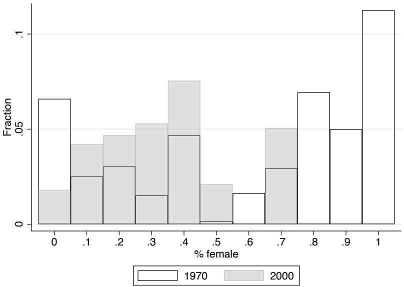

- **Routinization: displacement of routine occupations by automation**

College occupations

Research Question

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- Challenge: occupation prospects are endogenous

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  2. Over time: non-college job prospects deteriorated
- Challenge: occupation prospects are endogenous
- This paper uses automation as a shifter of non-college job opportunities
  - Premise: automation disproportionately displaced female non-college occupations
  - Approach: shift-share instruments to isolate labor demand for routine work

Overview

1. Instrument: Administrative share based on job posting data (1950-2000)
   - Labor markets with administratively-intense industries should undergo more routinization
   - Capture shifts in *labor demand* due to routinization

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   - Capture shifts in *labor demand* due to routinization
   - Routinization $\uparrow$ female enrollment, but not nec. male enrollment

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2. Structural approach complements IV approach:
    - Explicitly model mechanisms for individual decisions
    - Quantify the changes in college enrollment due to routinization:
        - 4 pp (44%) growth in female enrollment, 1.6 pp growth in male enrollment

Data

Data and Measurement

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  - Sample size permits examining occupation/industry-level changes by commuting zone-year

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  - Task content of occupations: routine, manual, abstract
  - Measure of automation susceptibility: Routine Task Intensity (RTI)

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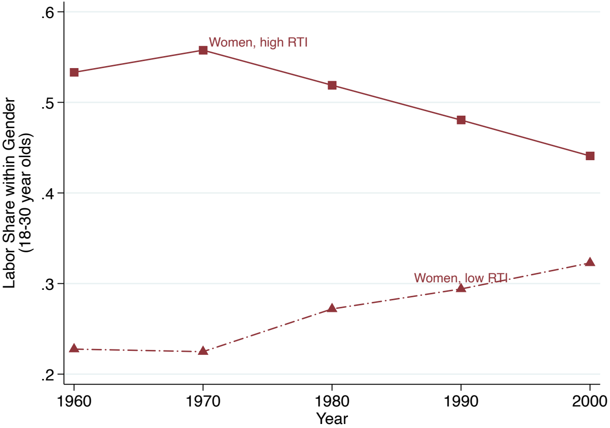
  - Administrative activities listed in job postings for each year from 1940 to 2000
- Structural Model: National Longitudinal Survey of Youth (1979)

Descriptive Evidence on Routinization

Decline in labor share of high-RTI occupations for women

Employment changes over time, by high and low RTI



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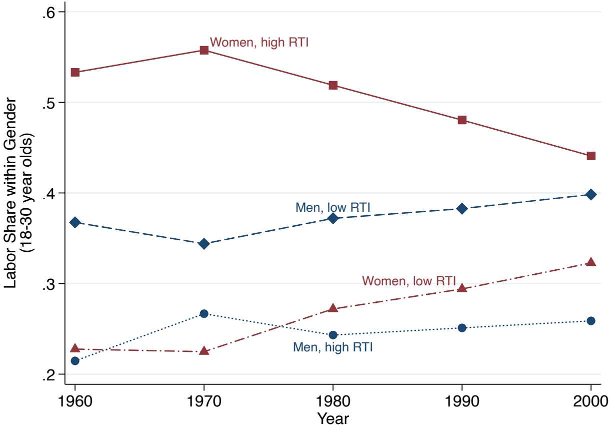
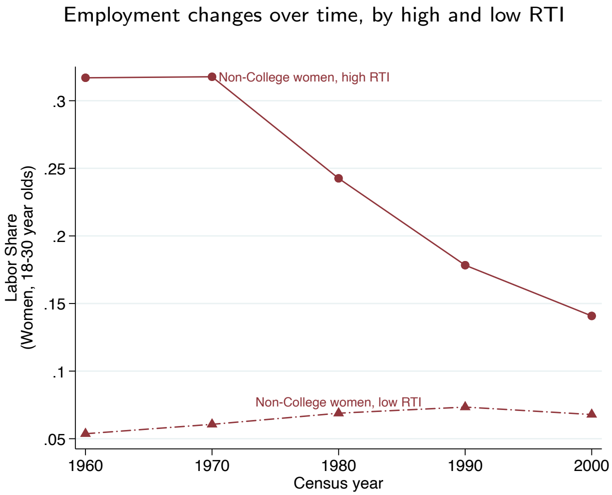


Decline in RTI share affects college-going for women



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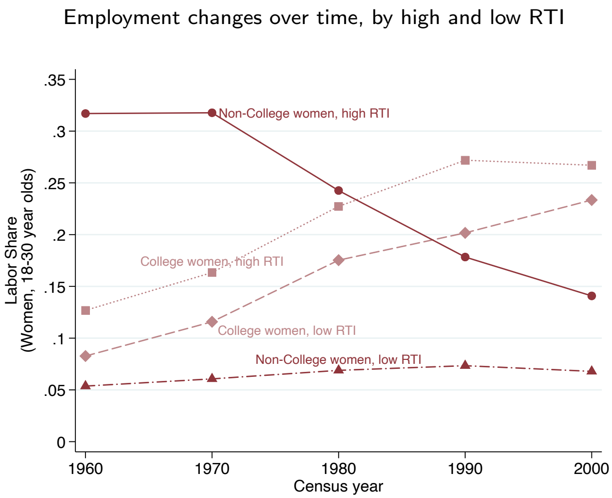

Two Stage Least Squares Approach

Job Posting IV

Newspaper job postings from Atalay et al. (2020):

$$\text{admin share}_{ct} = \sum_{i=1}^{I} E_{i,c,1950} \frac{\sum_k L_{ikt} \mathbf{1}(\text{admin}_{kt} > \text{admin}_{1950}^{P66})}{\sum_k L_{ikt}} \tag{1}$$

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- Intuition: commuting zones with high initial administrative shares experience more routinization over time
  - Wilmington, DE (legal industry)
  - Detroit, MI (manufacturing industry)

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- Identifying assumption: administrative share in national industry level can only affect college-going in commuting zone through routinization
  - Shift-share IV framework: industry-level shocks as good as random (Adao et al. 2019; Borusyak et al., 2018)
  - Standard error correction to account for correlated shocks across industries (Adao et al., 2019)

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- **Controls:**
  - male and female labor force participation (25-65 year olds)
  - predicted share of manual-intensive occupations
  - 10-year lagged services, manufacturing, retail, mining
  - race, gender, age, commuting zone, year, census controls
  - some specifications: median cognitive earnings, lagged routine share

Regression Equation

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First Stage Regression of Routinization on Instruments

	Routinization			
	(1)	(2)	(3)	(4)
Routinizability IV	0.387	0.383	0.388	0.383
	(0.026)***	(0.027)***	(0.027)***	(0.027)***
F-statistic	214.572	204.993	204.654	201.452
Observations	3610	3610	3610	3610
Commuting zone FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Median cognitive earnings		Yes		Yes
Lagged RTI share			Yes	Yes

Notes: First stage regression of routinization on instruments. Standard errors are clustered at the two-digit industry level and adjusted using the correction procedure of AKM (2019). Olea-Pflueger F-statistics reported using AKM (2019) standard errors. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

IV Regression: Routinization ⇒ growth in female enrollment

Second Stage Regressions

	College Enrollment			
	(1)	(2)	(3)	(4)
	A: Second Stage Regression, Women			
Routinization	0.578	0.606	0.578	0.606
	(0.163)***	(0.166)***	(0.160)***	(0.161)***
	[0.258,0.898]	[0.281,0.931]	[0.265,0.891]	[0.291,0.922]
F-statistic	214.572	204.993	204.654	201.452
Observations	3610	3610	3610	3610
	B: Second Stage Regression, Men			
Routinization	0.436	0.444	0.436	0.444
	(0.236)*	(0.238)*	(0.232)*	(0.234)*
	[-0.026,0.898]	[-0.022,0.910]	[-0.019,0.891]	[-0.015,0.904]
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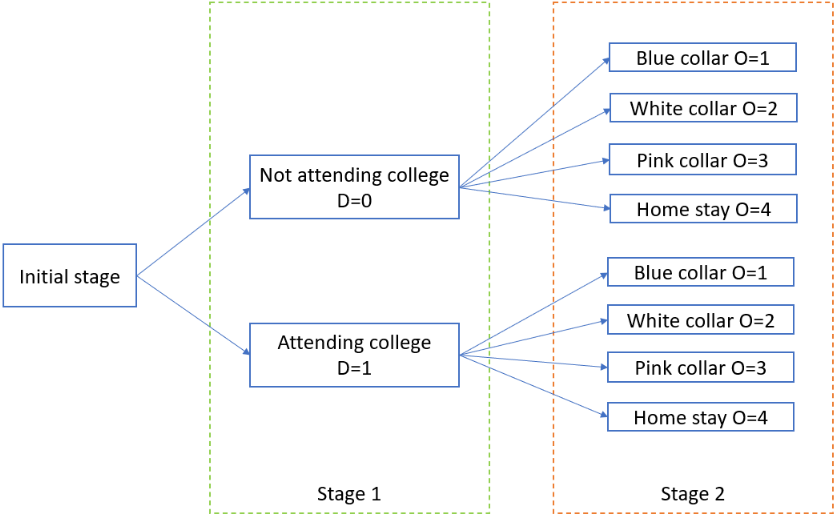
Structural Model

Structural approach: mechanisms

- Develop an explicit mechanism for how routinization affects individual decisions
  - Automation affects returns to occupations by influencing *skill prices*
  - Through impacting occupational returns, automation affects college enrollment decision
- Quantify the impact of routinization on college enrollment decisions
- Rationalize the polarization of non-college occupations
- Data: National Longitudinal Survey of Youth (1979)
  - Longitudinally link individual's education, occupation, and earnings over time
  - Skills: cognitive, mechanical, and administrative
    - Armed Services Vocational Aptitude Battery (ASVAB): cognitive, mechanical, administrative test scores (see Prada and Urzua, 2017)

2-period discrete choice model



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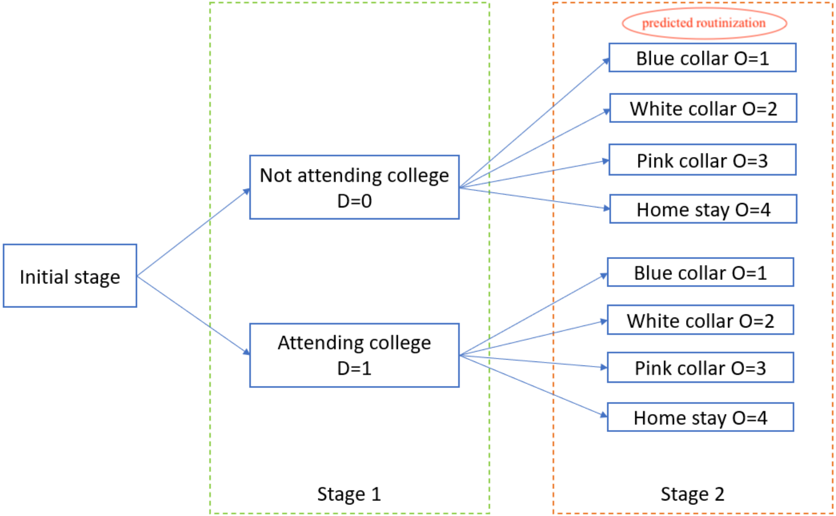

Model Assumptions

Model Simulations: Quantifying impact of routinization

	Women			Men		
	Baseline: 1980	Routinization in 2000	Change	Baseline: 1980	Routinization in 2000	Change
	(1)	(2)	(3)	(4)	(5)	(6)
Occupation choices						
White collar	0.404	0.610	0.206	0.392	0.434	0.042
Blue collar	0.038	0.049	0.011	0.485	0.452	-0.032
Pink collar	0.348	0.153	-0.195	0.048	0.050	0.002
Not working	0.209	0.188	-0.021	0.075	0.064	-0.012
Education choices						
High school	0.389	0.350	-0.040	0.481	0.465	-0.016
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- Male enrollment rises by 1.6 pp
    - Census data: 2 pp rise

Conclusion

- Gender polarization among non-college occupations $\Rightarrow$ gaps in outside options to attending college

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1. IV approach:
   - greater routinization $\Rightarrow$ displacement of women's non-college jobs
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   - Job polarization due to gender difference in skills & skill returns
   - Decline in pink-collar returns $\Rightarrow$ women shift from pink-collar to white-collar $\Rightarrow$ greater female college-going

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Thank you!

For questions or comments, please contact us at
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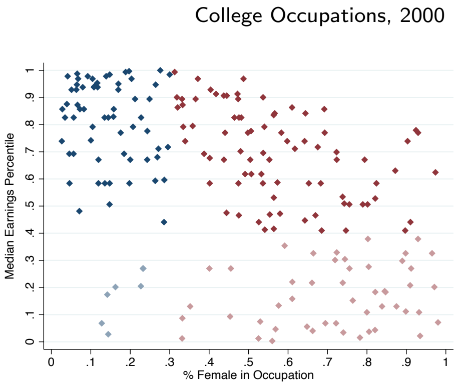
Appendix

Opposite missing quadrant in college occs

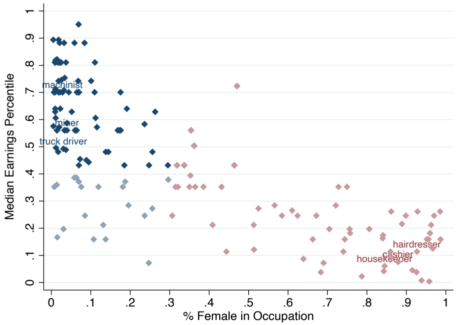


2000 Census. 18-30 year olds. College occupations are occupations with 50% of more workers who have ever enrolled in college.

Non-College Occupations, 2000

- Missing "quadrant" of low-paying male college occupations
- Consistent with sorting based on outside options

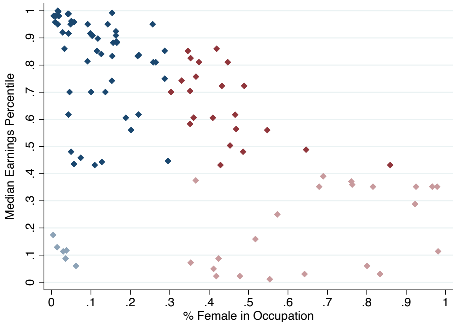
Non-College Occupations, 1970



Source: Census microdata, 1970. 18-30 year olds. Non-College occupations are occupations with 50% of more workers who have never enrolled in college.

Non-College Occupations, 2010

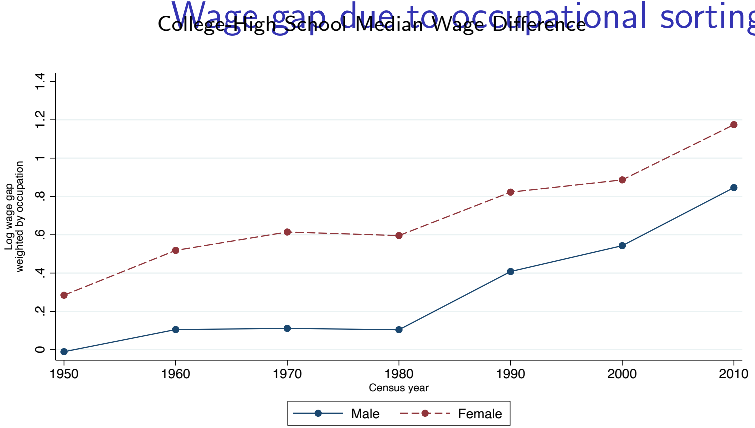
College Occupations, 1970



Source: Census microdata, 1970. 18-30 year olds. College occupations are occupations with 50% of more workers who have ever enrolled in college.

Non-College Occupations, 2010

Wage gap due to occupational sorting



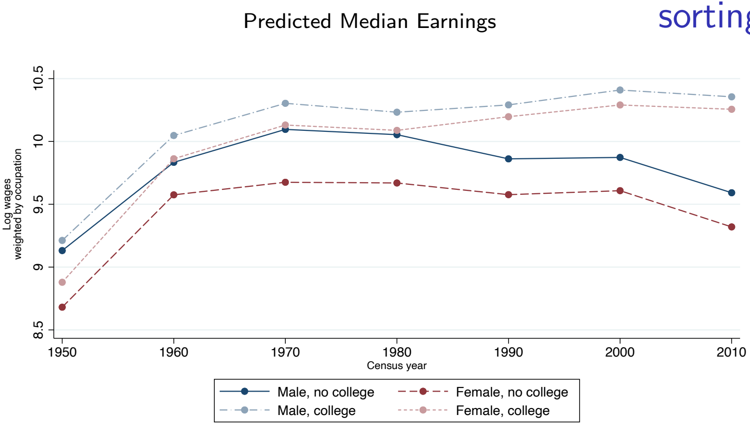
Source: Census and American Community Survey. 18-30 year olds. Difference in predicted median earnings for college and non-college workers, where

$$\text{predicted median earnings} = \sum_{o}^{O} \text{median earnings}_o \times \text{proportion in occupation o by gender}$$

.

Occupation Tables

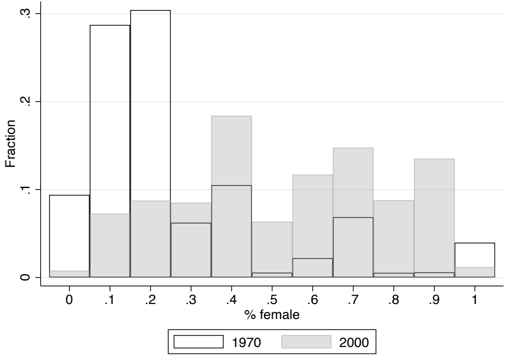
Predicted median earnings due to occupational sorting



Source: Census and American Community Survey. 18-30 year olds. Predicted median earnings for college and non-college workers computed as

$$\text{predicted median earnings} = \sum_{o}^{O} \text{median earnings}_o \times \text{proportion in occupation o by gender}$$

Increase in gender-equal college occupations over time



Source: IPUMS decadal census microdata (1970) and ACS data (2010). 18-30 year olds.

Non-College Occupations
Occupations by Education, Model

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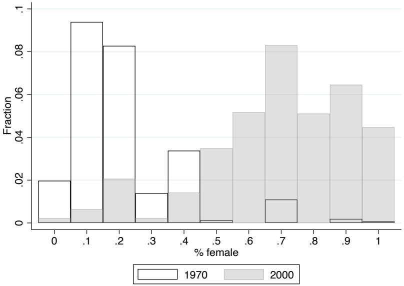
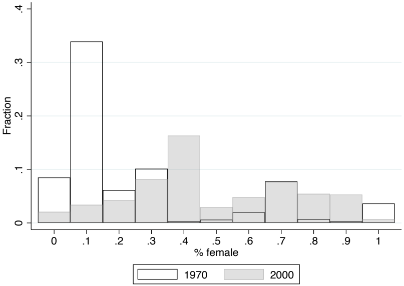
College Occupations, by RTI



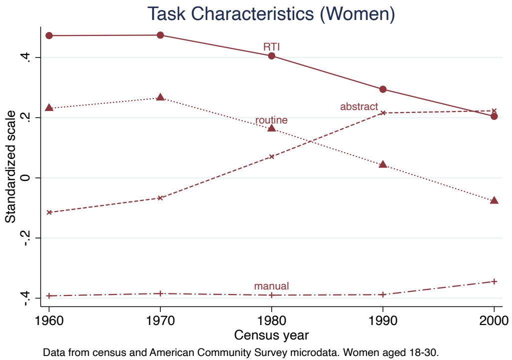


Source: IPUMS decadal census microdata (1970) and ACS data (2010). 18-30 year olds.

Non-college occupations

Women's RTI over time

Routine Task Intensity (RTI) in Labor Market



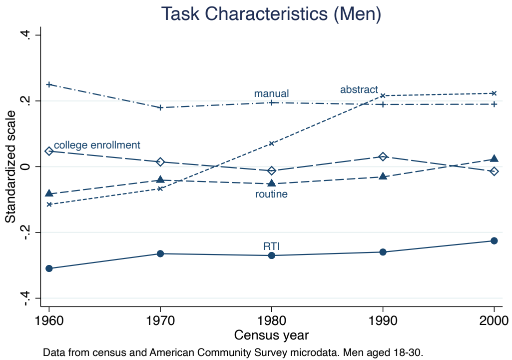
Source: IPUMS decadal census data for 1950-2000; American Community Survey yearly data for 2001-2005. 18-30 year olds.

$$RTI = \ln(\text{routine}) - \ln(\text{manual}) - \ln(\text{abstract})$$

RTI, main

Men's RTI over time

Routine Task Intensity (RTI) in Labor Market



Source: IPUMS decadal census data for 1950-2000; American Community Survey yearly data for 2001-2005. 18-30 year olds.

$$RTI = \ln(\text{routine}) - \ln(\text{manual}) - \ln(\text{abstract})$$

RTI, main

Regression equations

First stage regression:

$$\text{routinization}_{ct} = \alpha_0 + \alpha_1 \text{admin share}_{ct} + \alpha_2 X_{ct} + \phi_t + \theta_c + e_{ct} \tag{2}$$

- $\text{routinization}_{ct} = \text{RTI share}_{c,1950} - \text{RTI share}_{ct}$
- $\text{RTI share}_{c,1950}$: share of high RTI occs

Regression equations

First stage regression:

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- $\text{routinization}_{ct} = \text{RTI share}_{c,1950} - \text{RTI share}_{ct}$
- $\text{RTI share}_{c,1950}$: share of high RTI occs

Second stage regression:

$$Y_{ct} = \beta_0 + \beta_1 \widetilde{\text{routinization}}_{ct} + \beta_2 X_{ct} + \phi_t + \theta_c + \epsilon_{ct} \tag{3}$$

- Y_{ct} - female & male enrollment
- X_{ct} - commuting zone-year level controls

IV equation

Robustness

Second Stage Regressions, Additional Specifications

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	A: Female Enrollment							
Routinization	0.495	0.607	0.628	0.736	0.504	0.365	0.548	0.784
	(0.167)***	(0.158)***	(0.161)***	(0.242)***	(0.126)***	(0.145)**	(0.145)***	(0.145)***
	[0.167,0.822]	[0.297,0.917]	[0.312,0.944]	[0.263,1.210]	[0.256,0.752]	[0.080,0.650]	[0.213,0.884]	[0.350,1.219]
F-statistic	137.280	205.558	182.001	51.040	103.421	203.540	161.233	111.715
Observations	3610	3600	3610	3610	3610	3610	3610	3610
	B: Male Enrollment							
Routinization	0.315	0.503	0.441	0.540	0.218	0.254	0.432	0.616
	(0.266)	(0.234)**	(0.238)*	(0.315)*	(0.174)	(0.196)	(0.196)	(0.196)*
	[-0.207,0.838]	[0.044,0.961]	[-0.025,0.907]	[-0.077,1.157]	[-0.123,0.558]	[-0.129,0.638]	[-0.101,0.964]	[-0.048,1.280]
F-statistic	137.280	205.558	182.001	51.040	103.421	203.540	161.233	111.715
Observations	3610	3600	3610	3610	3610	3610	3610	3610
Minimum controls	✓							
Excluding Boston and NYC		✓						
Control for abstract occupation share			✓					
RTI share: non-college workers	✓	✓	✓		✓	✓	✓	✓
RTI share: college and non-college workers				✓				
IV: Administrative Share (top third)	✓	✓	✓	✓				
IV: Routine Share					✓			
IV: Administrative Share (top half)						✓		
IV: Administrative Activities							✓	
IV: Clerical Requirements								✓

Standard errors are clustered at the two-digit industry level and adjusted using the correction procedure of AKM (2019). Montiel Olea-Pflueger F-statistics reported using AKM (2019) standard errors. Anderson-Rubin (1949) confidence intervals reported using AKM (2019) correction. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

◂ 2SLS Results

Robustness

Second Stage Regressions, Additional Specifications

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Minimum controls	✓							
Excluding Boston and NYC		✓						
Control for abstract occupation share			✓					
RTI share: non-college workers	✓	✓	✓		✓	✓	✓	✓
RTI share: college and non-college workers				✓				
IV: Administrative Share (top third)	✓	✓	✓	✓				
IV: Routine Share					✓			
IV: Administrative Share (top half)						✓		
IV: Administrative Activities							✓	
IV: Clerical Requirements								✓

Standard errors are clustered at the two-digit industry level and adjusted using the correction procedure of AKM (2019). Montiel Olea-Pflueger F-statistics reported using AKM (2019) standard errors. Anderson-Rubin (1949) confidence intervals reported using AKM (2019) correction. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

◂ 2SLS Results

Parametric assumptions (1/2)

Period 2: Occupation

$$U(O_i|D_i) = \underbrace{Y(O_i|D_i)}_{\text{earnings}} + \underbrace{P(O_i|D_i)}_{\text{nonpecuniary returns}}$$

Parametric assumptions (1/2)

Period 2: Occupation

$$U(O_i|D_i) = \underbrace{Y(O_i|D_i)}_{\text{earnings}} + \underbrace{P(O_i|D_i)}_{\text{nonpecuniary returns}}$$

where

- $\theta_i = \{\theta_{ci}, \theta_{si}, \theta_{mi}\}$ is a vector of skills
- D_i: whether have college degree
- O_i: occupations (white, blue, pink, home)
- X_i: background characteristics

Parametric assumptions (1/2)

Period 2: Occupation

$$U(O_i|D_i) = \underbrace{Y(O_i|D_i)}_{\text{earnings}} + \underbrace{P(O_i|D_i)}_{\text{nonpecuniary returns}}$$

where

$$Y(O_i|D_i) = X_i^Y \alpha_O^g + D_i \alpha_{OD}^g + \epsilon_{O,D,i}^Y +$$
$$\theta_i(\alpha_{O\theta}^{g,0} + \alpha_{O\theta}^{g,1} \widetilde{\text{routinization}}_{c(i),t}) + \theta_i D_i(\alpha_{OD\theta}^{g,0} + \alpha_{OD\theta}^{g,1} \widetilde{\text{routinization}}_{c(i),t})$$

- $\theta_i = \{\theta_{ci}, \theta_{si}, \theta_{mi}\}$ is a vector of skills
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Parametric assumptions (1/2)

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where

$$Y(O_i|D_i) = X_i^Y \alpha_O^g + D_i \alpha_{OD}^g + \epsilon_{O,D,i}^Y +$$
$$\theta_i(\alpha_{O\theta}^{g,0} + \alpha_{O\theta}^{g,1} \widetilde{\text{routinization}}_{c(i),t}) + \theta_i D_i(\alpha_{OD\theta}^{g,0} + \alpha_{OD\theta}^{g,1} \widetilde{\text{routinization}}_{c(i),t})$$

$$P(O_i|D_i) = X_i^Y \beta_O^g + D_i \beta_{OD}^g + \epsilon_{O,D,i}^P +$$
$$\theta_i(\beta_{O\theta}^{g,0} + \beta_{O\theta}^{g,1} \widetilde{\text{routinization}}_{c(i),t}) + \theta_i D_i(\beta_{OD\theta}^{g,0} + \beta_{OD\theta}^{g,1} \widetilde{\text{routinization}}_{c(i),t})$$

- $\theta_i = \{\theta_{ci}, \theta_{si}, \theta_{mi}\}$ is a vector of skills
- D_i: whether have college degree
- O_i: occupations (white, blue, pink, home)
- X_i: background characteristics

Parametric assumptions (2/2)

Period 1: Education

$$D_i = \mathbf{1}[V_i^1 + \xi_i^D > V_i^0]$$

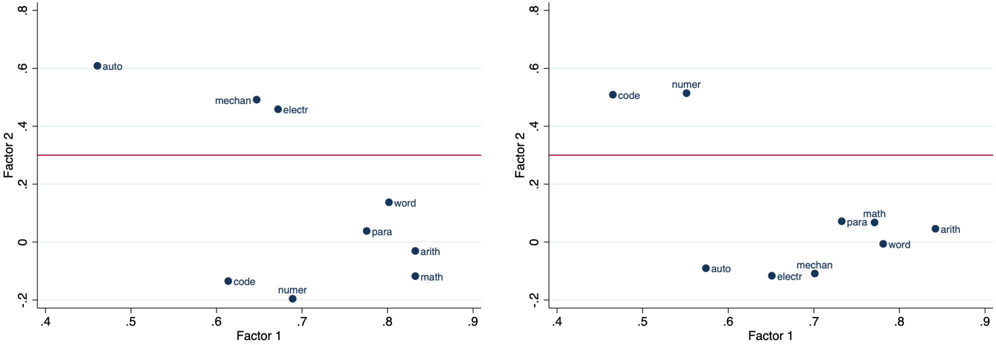
$$V_i^0 = E \max_{O_i} U(O_i | D_i = 0)$$

$$V_i^1 = X_i^D \lambda_X^g + \theta_i \lambda_\theta^g + \rho E \max_{O_i} U(O_i | D_i = 1)$$

◂ Model Diagram

Exploratory Factor Loadings

(a) Male (b) Female



Skill Distributions

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Occupational Returns