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

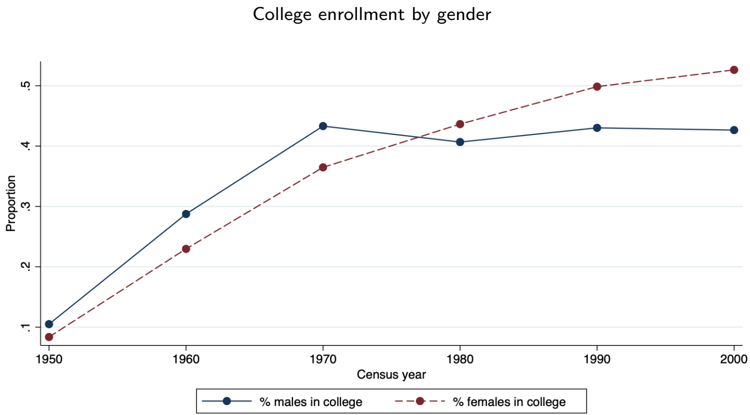
Amanda Chuan[1] Weilong Zhang[2]

[1]Michigan State University

[2]University of Cambridge

EEA-ESEM, Aug 29, 2023

Women overtook men in college enrollment

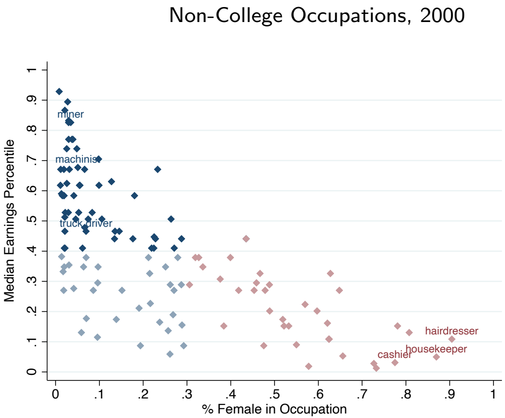


Source: IPUMS decadal census data for 1950-2000; American Community Survey yearly data for 2001-2010. 18-30 year olds.

- 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

2/17

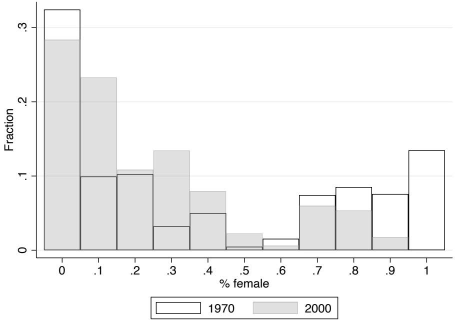
"Missing quadrant" of high-paying female non-college occs



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

3/17

Decline in women's non-college occupations over time

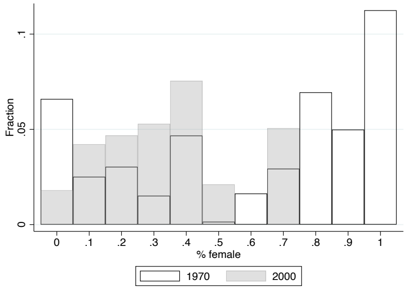


Source: IPUMS decadal census microdata (1970) and ACS data (2010). 18-30 year olds.

- 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

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

(a) Routine Occupations

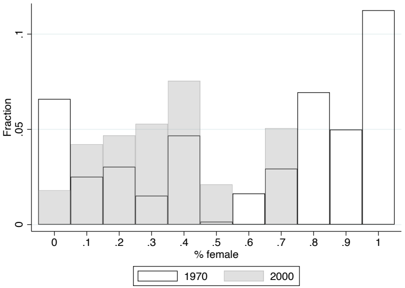


- 1970: among high routine occupations, most were female-dominated
- By 2000: no more high routine female-dominated occupations

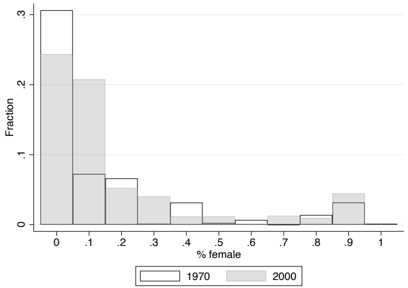
College occupations

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

(a) Routine Occupations



(b) Non-routine Occupations



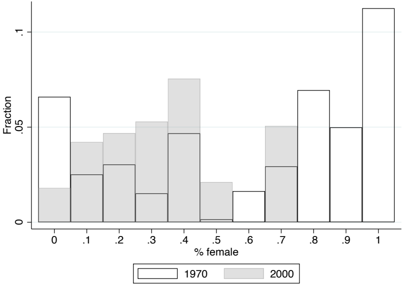
- 1970: among high routine occupations, most were female-dominated
- By 2000: no more high routine female-dominated occupations
- Non-routine occupations: little change over time

College occupations

4/17

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

(a) Routine Occupations



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

College occupations

Research Question

- Did non-college jobs contribute to college gender gap?

Research Question

- Did non-college jobs contribute to college gender gap?
- Two stylized facts for non-college female workers
  1. Cross-sectionally: Missing quadrant of high-paying occupations
  2. Over time: non-college job prospects deteriorated

Research Question

- Did non-college jobs contribute to college gender gap?
- Two stylized facts for non-college female workers
  1. Cross-sectionally: Missing quadrant of high-paying occupations
  2. Over time: non-college job prospects deteriorated
- Challenge: occupation prospects are endogenous

Research Question

- Did non-college jobs contribute to college gender gap?
- Two stylized facts for non-college female workers
  1. Cross-sectionally: Missing quadrant of high-paying occupations
  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

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
   - Routinization $\uparrow$ female enrollment, but not nec. male enrollment

Overview

1. Instrument: Administrative share based on job posting data (1950-2000)

2. Structural approach complements IV approach:

Overview

1. Instrument: Administrative share based on job posting data (1950-2000)

2. Structural approach complements IV approach:
    - Explicitly model mechanisms for individual decisions
    - Quantify the changes in college enrollment due to routinization:

Overview

1. Instrument: Administrative share based on job posting data (1950-2000)

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

- Census (1950-2000)
  - Sample size permits examining occupation/industry-level changes by commuting zone-year

Data and Measurement

- Census (1950-2000)
  - Sample size permits examining occupation/industry-level changes by commuting zone-year
- Autor and Dorn (2013) measures of automation susceptibility
  - Task content of occupations: routine, manual, abstract
  - Measure of automation susceptibility: Routine Task Intensity (RTI)

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

Data and Measurement

- Census (1950-2000)
  - Sample size permits examining occupation/industry-level changes by commuting zone-year
- Autor and Dorn (2013) measures of automation susceptibility
  - Task content of occupations: routine, manual, abstract
  - Measure of automation susceptibility: Routine Task Intensity (RTI)

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

- Instrumental variation: newspaper job posting data from Atalay et al. (2020)
  - Administrative activities listed in job postings for each year from 1940 to 2000

Data and Measurement

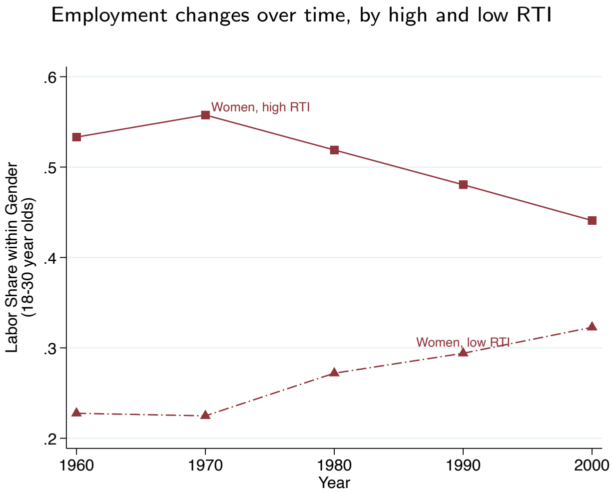
- Census (1950-2000)
  - Sample size permits examining occupation/industry-level changes by commuting zone-year
- Autor and Dorn (2013) measures of automation susceptibility
  - Task content of occupations: routine, manual, abstract
  - Measure of automation susceptibility: Routine Task Intensity (RTI)

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

- Instrumental variation: newspaper job posting data from Atalay et al. (2020)
  - Administrative activities listed in job postings for each year from 1940 to 2000
- Structural Model: National Longitudinal Survey of Youth (1979)

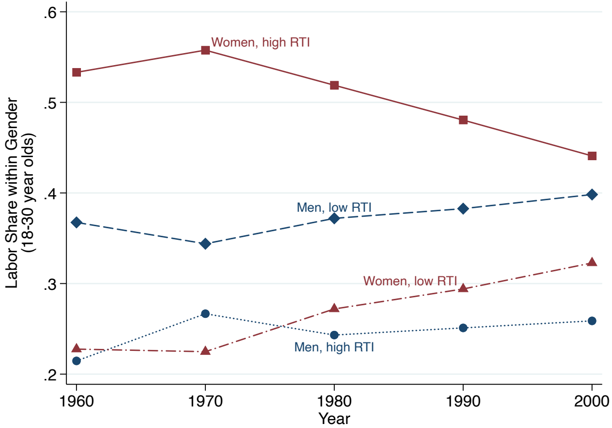
Descriptive Evidence on Routinization

Decline in labor share of high-RTI occupations for women

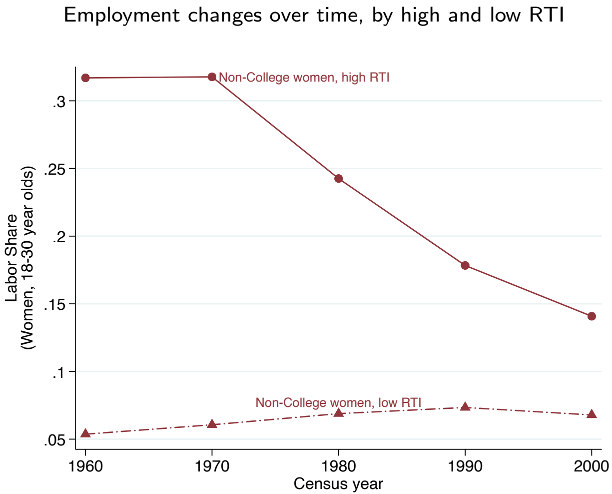


Decline in labor share of high-RTI occupations for women

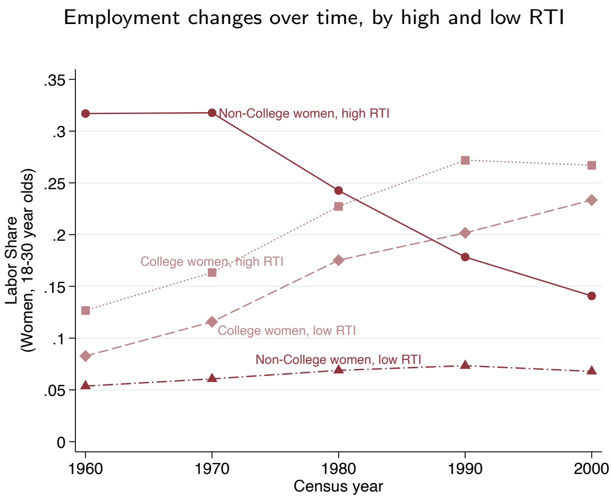
Employment changes over time, by high and low RTI



Decline in RTI share affects college-going for women



Decline in RTI share affects college-going for women



Two Stage Least Squares Approach

Job Posting IV

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

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

- admin share$_{ct}$: predicted administrative share in commuting zone c
- $E_{i,c,1950}$: share of industry i in commuting zone c
- admin$_{kt}$: administrative activity in occupation k

Job Posting IV

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

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

- admin share_{ct}: predicted administrative share in commuting zone c
- $E_{i,c,1950}$: share of industry i in commuting zone c
- admin_{kt}: administrative activity in occupation k

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

Job Posting IV

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

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

- admin share_{ct}: predicted administrative share in commuting zone c
- $E_{i,c,1950}$: share of industry i in commuting zone c
- admin_{kt}: administrative activity in occupation k

- 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)

Job Posting IV

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

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

- admin share$_{ct}$: predicted administrative share in commuting zone c
- $E_{i,c,1950}$: share of industry i in commuting zone c
- admin$_{kt}$: administrative activity in occupation k

- **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

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 $\Rightarrow$ 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]
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: Standard errors are clustered at the two-digit industry level and adjusted using the correction procedure of AKM (2019). Montiel Olea-Pflueger first stage F-statistics reported using AKM (2019) standard errors. The second stage estimates include Anderson-Rubin (1949) weak instrument robust confidence intervals using the AKM (2019) correction. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

13/17

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]
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: Standard errors are clustered at the two-digit industry level and adjusted using the correction procedure of AKM (2019). Montiel Olea-Pflueger first stage F-statistics reported using AKM (2019) standard errors. The second stage estimates include Anderson-Rubin (1949) weak instrument robust confidence intervals using the AKM (2019) correction. $^{*}\ p < 0.10$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$.

13/17

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]
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: Standard errors are clustered at the two-digit industry level and adjusted using the correction procedure of AKM (2019). Montiel Olea-Pflueger first stage F-statistics reported using AKM (2019) standard errors. The second stage estimates include Anderson-Rubin (1949) weak instrument robust confidence intervals using the AKM (2019) correction. $^{*}\ p < 0.10$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$.

13/17

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]
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: Standard errors are clustered at the two-digit industry level and adjusted using the correction procedure of AKM (2019). Montiel Olea-Pflueger first stage F-statistics reported using AKM (2019) standard errors. The second stage estimates include Anderson-Rubin (1949) weak instrument robust confidence intervals using the AKM (2019) correction. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

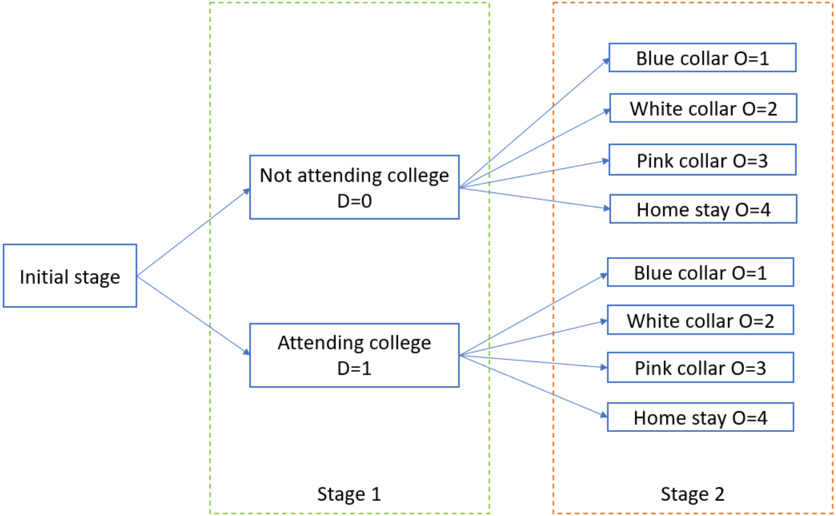
13/17

Structural Model

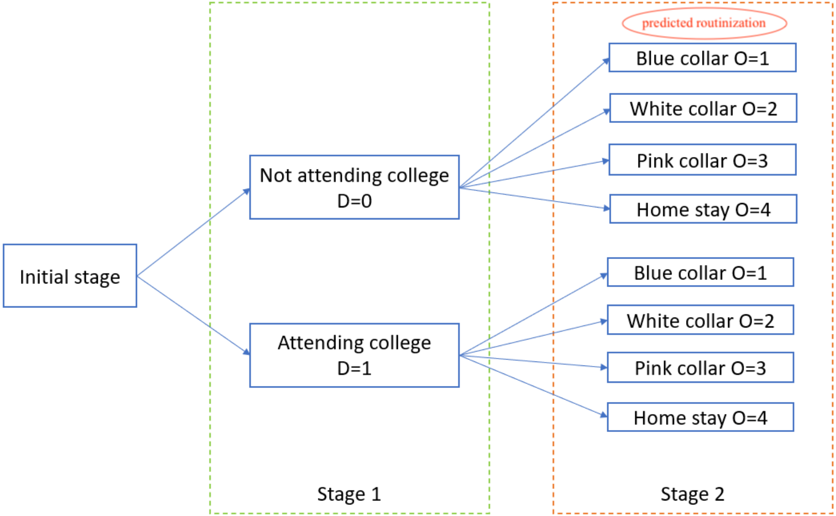
Structural approach: mechanisms

- 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



2-period discrete choice model



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
College	0.611	0.650	0.040	0.519	0.535	0.016

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
College	0.611	0.650	0.040	0.519	0.535	0.016

- Female enrollment rises by 4 pp
  - Census data: 9 pp rise

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
College	0.611	0.650	0.040	0.519	0.535	0.016

- Female enrollment rises by 4 pp
  - Census data: 9 pp rise
- 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

Overview of Results

1. IV approach:
    - greater routinization $\Rightarrow$ displacement of women's non-college jobs
    - decline in outside options $\Rightarrow \uparrow$ female enrollment
    - no systematic effects for men

Conclusion

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

Overview of Results

1. IV approach:
   - greater routinization $\Rightarrow$ displacement of women's non-college jobs
   - decline in outside options $\Rightarrow \uparrow$ female enrollment
   - no systematic effects for men

17/17

Conclusion

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

Overview of Results

1. IV approach:

2. Structural approach: Routinization $\downarrow$ women's non-college occupational returns
   - 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

Conclusion

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

Overview of Results

1. IV approach:

2. Structural approach: Routinization $\downarrow$ women's non-college occupational returns
   - 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

Thank you!

For questions or comments, please contact us at
achuan@msu.edu or wz301@cam.ac.uk

References

- Acemoglu, D., Autor, D., 2011. Skills, Tasks, and Technologies: Implications for Employment and Earnings. Handbook of Labor Economics Vol. 4b.
- Acemoglu, D., Autor, D., Hazell, J., Restrepo, P., 2020. AI and Jobs: Evidence from Online Vacancies. NBER Working Paper 28257.
- Acemoglu, D., Restrepo, P., 2019. Automation and New Tasks: How Technology Displaces and Reinstates Labor. NBER Working Paper 25684.
- Acemoglu, D., Restrepo, P., 2020. Robots and Jobs: Evidence from US Labor Markets. Journal of Political Economy 128(6), 2188-2242.
- Adao, R., Kolesar, M., Morales, E., 2019. Shift-Share Designs: Theory and Inference. Quarterly Journal of Economics 1949-2010.
- Atalay, E., Phongthiengtham, P., Sotelo, S., Tannenbaum, D., 2020. The Evolution of Work in the United States. American Economic Journal: Applied Economics 12(2), 1-34.
- Atkin, D., 2016. Endogenous Skill Acquisition and Export Manufacturing in Mexico. American Economic Review 106(8), 2046-2085.
- Autor, D., 2015. Why Are There Still So Many Jobs? The History and Future of Workplace Automation. Journal of Economic Perspectives 29(3), 3-30.
- Autor, D., Dorn, D., 2013. The Growth of Low-Skill Service Jobs and the Polarization of the US Labor Market. American Economic Review 103(5): 1553-1597.
- Autor, D., Levy, F., Murnane, R., 2003. The Skill Content of Recent Technological Change: An Empirical Exploration. Quarterly Journal of Economics 118(4), 1279-1333.
- Autor, D., Wasserman, M., 2013. Wayward Sons: The Emerging Gender Gap in Labor Markets and Education. Third Way, March 2013.
- Becker, G., Hubbard, W., Murphy, K., 2010. Explaining the Worldwide Boom in the Higher Education of Women. Journal of Human Capital 4(3): 203-241
- Bertrand, M., Pan, J., 2013. The Trouble with Boys: Social Influences and the Gender Gap in Disruptive Behavior. American Economic Journal: Applied Economics 2013 5(1), 32-64.
- Black, S., Spitz-Oener, 2010. Explaining Women's Success: Technological Change and the Skill Content of Women's Work. The Review of Economics and Statistics 92(1), 187-194.
- Borusyak, K., Hull, P., Jaravel, X., 2019. Quasi-Experimental Shift-Share Research Designs.
- Bresnahan, T., Brynjolfsson, E., Hitt, L., 2002. Information Technology, Workplace Organization, and the Demand for Skilled Labor: Firm-Level Evidence. Quarterly Journal of Economics 117(1), 339-376.
- Bronson, M. Degrees Are Forever: Marriage, Educational Investment, and Lifecycle Labor Decisions of Men and Women.
- Brynjolfsson, E., Hitt, L., 2000. Beyond Computation: Information Technology, Organizational Transformation and Business Performance. Journal of Economic Perspectives 14(4), 23-48.
- Bronson, M., 2015. Degrees are Forever: Marriage, Educational Investment, and Lifecycle Labor Decisions of Men and Women.
- Buchmann, C., DiPrete, T., 2006. The Growing Female Advantage in College Completion: The Role of Family Background and Academic Achievement. American Sociological Review 71(4), 515-541.

References

- Carrell, S., Sacerdote, B., 2017. Why Do College Going Interventions Work? American Economic Journal: Applied Economics 9(3), 124-151.
- Cascio, E., Narayan, A., 2015. Who Needs a Fracking Education? The Educational Response to Low-Skill Biased Technological Change. NBER Working Paper 21359.
- Charles, K., Hurst, E., Notowidigdo, M., 2016. Housing Booms and Busts, Labor Market Opportunities, and College Attendance. American Economic Review 108(10): 2947-94.
- Charles, K., Luoh, M., 2003. Gender Differences in Completed Schooling. The Review of Economics and Statistics 85(3), 559-577.
- Cortes, G., Jaimovich, N., Nekarda, C., Siu, H., 2014. The Micro and Macro of Disappearing Routine Jobs: A Flows Approach. NBER Working Paper 20307.
- Cortes, G., Jaimovich, N., Siu, H., 2016. Disappearing Routine Jobs: Who, How, and Why? NBER Working Paper 22918.
- Chiappori, P., Iyigun, M., Weiss, Y., 2009. Investment in Schooling and the Marriage Market. The American Economic Review 99(5), 1689-1713.
- Chiappori, P., Salanie, B., Weiss, Y., 2015. Partner Choice and the Marital College Premium: Analyzing Marital Patterns over Several Decades.
- Dougherty, C., 2005. Why Are the Returns to Schooling Higher for Women than for Men? Journal of Human Resources 40(4), 969-988.
- Dillender, M., Forsythe, E., 2019. Computerization of White Collar Jobs.
- Doms, M., Lewis, E., 2006. Labor Supply and Personal Computer Adoption.
- Manhood (2015, July 6). *The Economist.* Retrieved from `https://www.economist.com/`
- The Weaker Sex (2016, May 29). *The Economist.* Retrieved from `https://www.economist.com/`
- Feigenbaum, J., Gross, D., 2020. Automation and the Fate of Young Workers: Evidence from Telephone Operation in the Early 20th Century. NBER Working Paper 28061.
- Frey, C., Osborne, M., 2013. The Future of Employment: How Susceptible are Jobs to Computerisation?
- Goldin, C., Katz, L., 2008. *The Race Between Education and Technology.* Cambridge, MA: Harvard University Press.
- Goldin, C., Katz, L., 2009. The Race Between Education and Technology: The Evolution of U.S. Wage Differentials, 1890-2004. NBER Working Paper 12984.
- Goldin, C., Katz, L., Kuziemko, I., 2006. The Homecoming of American College Women: The Reversal of the College Gender Gap. Journal of Economic Perspectives 20(4): 133-156.
- Goos, M., Manning, A., Salomons, A., 2009. Job Polarization in Europe. American Economic Review 99(2), 58-62.
- Goos, M., Manning, A., Salomons, A., 2014. Explaining Job Polarization: Routine-Biased Technological Change and Offshoring. American Economic Review 104(8), 2509-2526.
- Greenwood, J., Seshadri, A., Yorukoglu, M., 2005. Engines of Liberation. The Review of Economic Studies 72(1), 109-133.

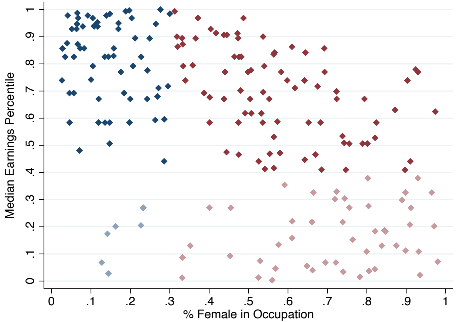
References

- Hershbein, B., Kahn, L., 2018. Do Recessions Accelerate Routine-Biased Technological Change? Evidence from Vacancy Postings. The American Economic Review 108(7), 1737-1772.
- Huang, L., 2013. A Revolution in Education: Determinants of the Gender Gap Reversal.
- Jacob, B., 2002. Where the boys aren't: non-cognitive skills, returns to school and the gender gap in higher education. Economics of Education Review 21, 589-598.
- Katz, L., Autor, D., 1999. Changes in the Wage Structure and Earnings Inequality. In *Handbook of Labor Economics* Vol. 3A, edited by Orley Ashenfelter and David E. Card, 1465-1555. Amsterdam: Elsevier B.V.
- Kovalenko, A., 2020. Natural Resource Booms, Human Capital and Earnings: Evidence from Linked Education and Employment Records.
- Lee, D., Wolpin, K., 2010. Accounting for wage and employment changes in the US from 1968-2000: A dynamic model of labor market equilibrium.
- Lindenlaub, I., 2016. Sorting Multidimensional Types: Theory and Application. Review of Economic Studies 84, 718-789.
- Lise, J., Postel-Vinay, F., 2016. Multidimensional Skills, Sorting, and Human Capital Accumulation.
- Low, C., 2019. A "Reproductive Capital" Model of Marriage Market Matching.
- Mosquera, R., 2019. A Blessing or a Curse? The Long-Term Effect of Resource Booms on Human Capital.
- Neilson, E., 2019. The Fracking Boom, Local Labor Market Opportunities, and College Attainment.
- Rendall, M., 2018. Brain versus Brawn: The Realization of Women's Comparative Advantage.
- Rosin, H., (2016, Dec. 29). The End of Men. *The Atlantic.* Retrieved from `https://www.theatlantic.com`
- Prada, M., Urzua, S., 2017. One Size Does Not Fit All: Multiple Dimensions of Ability, College Attendance and Earnings. Journal of Labor Economics 35(4): 953-990.
- Shah, M., Steinberg, B., 2015. Workfare and Human Capital Investment: Evidence from India. NBER Working Paper 21543.
- Shah, M., Steinberg, B., 2017. Drought of Opportunities: Contemporaneous and Long-Term Impacts of Rainfall Shocks on Human Capital. Journal of Political Economy 125(2), 527-561.
- Spitz-Oener, A., 2006. Technical Change, Job Tasks, and Rising Educational Demands: Looking outside the Wage Structure. Journal of Labor Economics 24(2), 235-270.
- Spitz-Oener, A., 2008. The Returns to Pencil Use Revisited. Industrial and Labor Relations Review 61(4), 502-517.
- Olivieri, E., 2014. Occupational Choice and the College Gender Gap.
- Welch, F., 2000. Growth in Women's Relative Wages and in Inequality among Men: One Phenomenon or Two? American Economic Review Papers & Proceedings 90(2), 444-449.
- Zhang, H., 2021. An Investment-and-Marriage Model with Differential Fecundity: On the College Gender Gap. Journal of Political Economy 129(5).

Appendix

Opposite missing quadrant in college occs

College Occupations, 2000

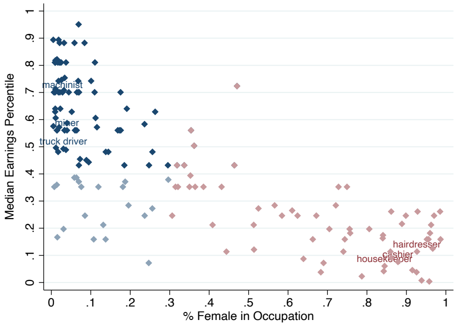


2000 Census. 18-30 year olds. College occupations are occupations with 50% of more workers who have ever enrolled in college.

Non-College Occupations, 2000

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

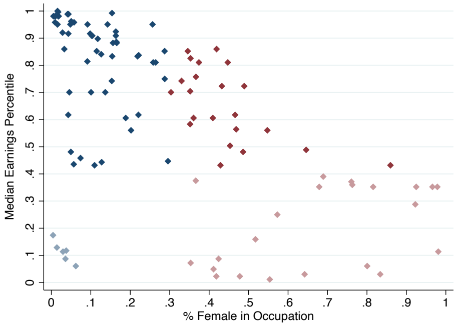
Non-College Occupations, 1970



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

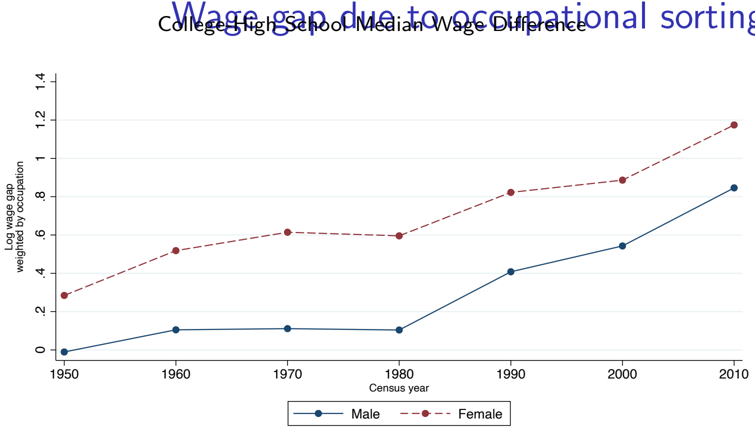
College Occupations, 1970



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



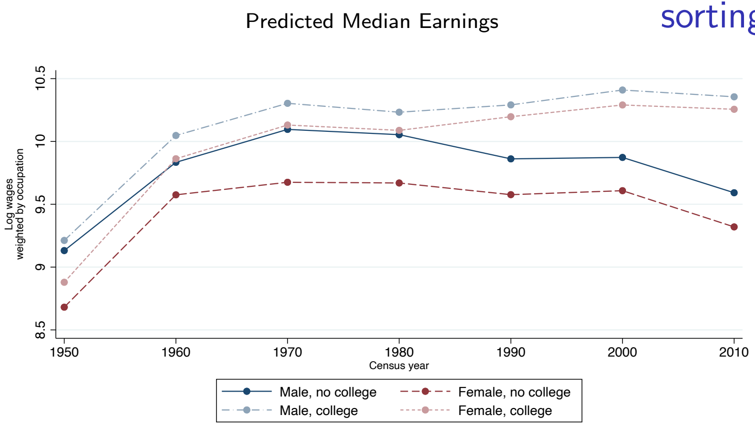
Source: Census and American Community Survey. 18-30 year olds. Difference in predicted median earnings for college and non-college workers, where

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

.

Occupation Tables

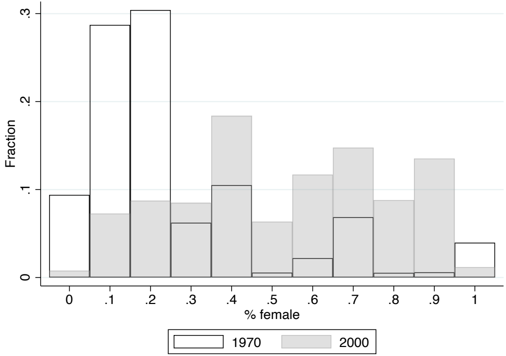
Predicted median earnings due to occupational sorting



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

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

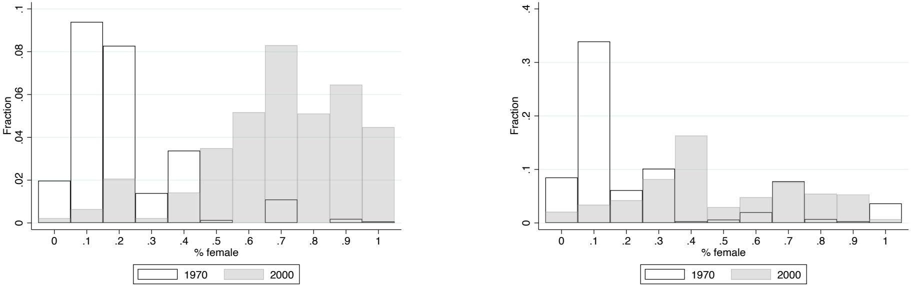
Increase in gender-equal college occupations over time



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

Non-College Occupations
Occupations by Education, Model

College Occupations, by RTI

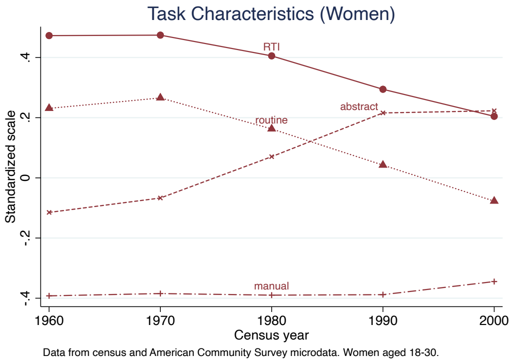


Source: IPUMS decadal census microdata (1970) and ACS data (2010). 18-30 year olds.

Non-college occupations

Women's RTI over time

Routine Task Intensity (RTI) in Labor Market



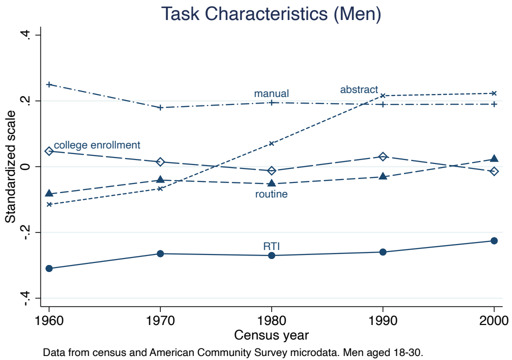
Source: IPUMS decadal census data for 1950-2000; American Community Survey yearly data for 2001-2005. 18-30 year olds.

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

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:

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

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

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

	(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

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
- 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

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

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

- $\theta_i = \{\theta_{ci}, \theta_{si}, \theta_{mi}\}$ 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

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

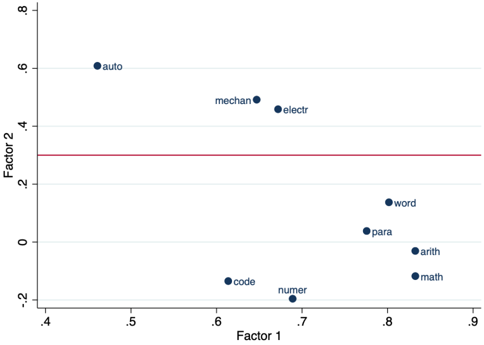
$$V_i^0 = E \max_{O_i} U(O_i | D_i = 0)$$

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

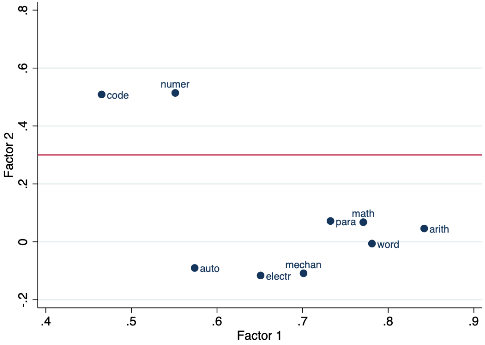
Model Diagram

Exploratory Factor Loadings

(a) Male



(b) Female



Skill Distributions

Occupational Returns