Automation and Gender: Implications for Occupational Segregation and the Gender Skill Gap

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Motivation

- Women have made significant gains in the labor market during the last few decades.
- In particular, occupational differences by gender have narrowed, although they remain significant. ▸ figure
- The gender gap in college education has reversed in favor of women since the early 1990s. ▸ figure
- Automation, particularly, computerization, has transformed the nature of work and the range of tasks that workers are engaged in.

Two Natural Questions

1. How did automation contribute to the changes in the employment structure of men and women, and consequently, the decline in occupational segregation?
2. What are the effects of automation on men's and women's decisions to invest in human capital? Did automation play some role in the women's relative educational gains over the past four decades?

This Paper

- Document key descriptive facts about the relationship between gender, occupation, and automation in the U.S. labor market from 1980 to 2017.
  - Specifically, examine how impact of automation and subsequent responses differ by gender.

- Study the causal effects of automation by exploiting variation in local labor market exposure to automation.
  - Effects on the occupational structure of men and women, and overall occupational segregation.
  - Gender differences in skill investments in response to automation.

- Explore potential channels for differential responses by gender (work in progress)
  - Growing complementarity between social skills and cognitive skills favoring women.
  - Gender differences in the ability to adapt to changes by retraining and upskilling.

Existing Work

- Large literature studying the relationship between computerization, job skill demands, and the structure of employment and wages.
  - Autor, Levy, and Murnane (ALM, 2003)
    - Task-based approach to identify jobs most affected by automation.
    - Declining price of computing in the 1980s–1990s associated with reductions in routine manual and cognitive tasks.
  - Autor and Dorn (2013)
    - Unified analysis of the role of automation in employment and wage polarization in the U.S. between 1980–2005.
    - Local labor markets specializing in routine tasks more likely to adopt computers, experience a growth in the low-skilled service sector, and inflows of skilled workers.
  - Also: Beaudry, Lewis, and Doms (2010), Goos et al. (2009, 2014), Goos and Manning (2007)

Existing Work

- Differential effects of computer adoption on men and women.
  - Women have comparative advantage in:
    - "Brains" vs. "brawn" (Welch, 2000)
    - People/social skills (Borghans et al., 2014; Deming, 2017)
  - Technological change favors women, thereby narrowing employment and wage gaps.
    - Time-series evidence: Black and Spitz-Oener (2010), Bacolod and Blum (2010), Autor and Wasserman (2013), etc.
    - Cross-city evidence: Beaudry and Lewis (2014) – Decline in gender wage gap since 1980 explained by changes in skill prices driven by PC adoption.
  - Role of social/interpersonal skills
    - Social skills are increasingly rewarded; computerization could explain the increasing the returns to complementarity between cognitive and social skills.
    - Borghans et al. (2014), Deming (2017), Cortes et al. (2020)

- Our innovation: Provide a comprehensive analysis of the differential effects of automation on the occupational structure and skill investments of men and women, and explore causal mechanisms.

Roadmap

1. Data and empirical strategy
2. Descriptive analysis
3. Cross-labor market analysis of the impact of automation on:
   - Employment structure by gender
   - Occupational segregation
   - Skill investments by gender
4. Implications for future waves of automation
5. Next steps

Empirical Approach

1. Descriptive analysis: Focus on cross-occupation variation in the relative importance of tasks that can be replaced by automation and relate this to changes over time in the occupational distribution by gender.

2. Causal exercise: Exploit cross-commuting zone (CZ) variation in the share of the labor force at baseline working in occupations with high automation risk.
   - Address the endogeneity of the occupational distribution at baseline with a Bartik instrument that uses the occupation and industry distributions across CZs in 1950.

Data I

- 1980 to 2000 U.S. Census, 2010 (2008–2010) and 2017 (2016–2018) ACS 3-year aggregate
- Main sample: Individuals age 18–64 who are employed in the civilian labor force and reported an occupation.
- Task composition of occupations:
  - Measures of routine, abstract, manual task inputs from Autor and Dorn (2013) – based on task requirements from 1977 DOT.
    - Routine: "set limits, tolerances, and standards" and "finger dexterity"
    - Manual: "eye-hand-foot coordination"
    - Abstract: "direction control and planning" and "GED Math"
  - Measures of social skills and cognitive inputs from Deming (2017) – based on O*NET data.
    - Social skills [4 items]: coordination, negotiation, persuasion, social perceptiveness
    - Cognitive/math intensity [3 items]: capture math reasoning requirements

Measures of Occupation-Level Automation Risk

- We follow Autor, Levy and Murnane (2003) in the use of a task-based approach:
  - Routine Tasks: follow precise, well-defined procedures
  - Abstract Tasks: creative, problem-solving, coordination
  - Manual Tasks: physical dexterity and flexible interpersonal communication

- ALM combines these measures into a routine task-intensity (RTI) index:

$$RTI = \ln(T_R) - \ln(T_M) - \ln(T_A)$$

Examples of Occupations with High and Low RTI

Occupations with the highest employment share in 1980 by RTI level	
High RTI	Secretaries and stenographers
	Bookkeepers, accounting and auditing clerks
	Assemblers of electrical equipment
	General office clerks
	Production checkers, graders, and sorters in manufacturing
Low RTI	Managers and administrators
	Truck, delivery, and tractor drivers
	Production supervisors or foremen
	Primary school teachers

Task Intensity of Major Occupation Groups

TABLE 2—TASK INTENSITY OF MAJOR OCCUPATION GROUPS

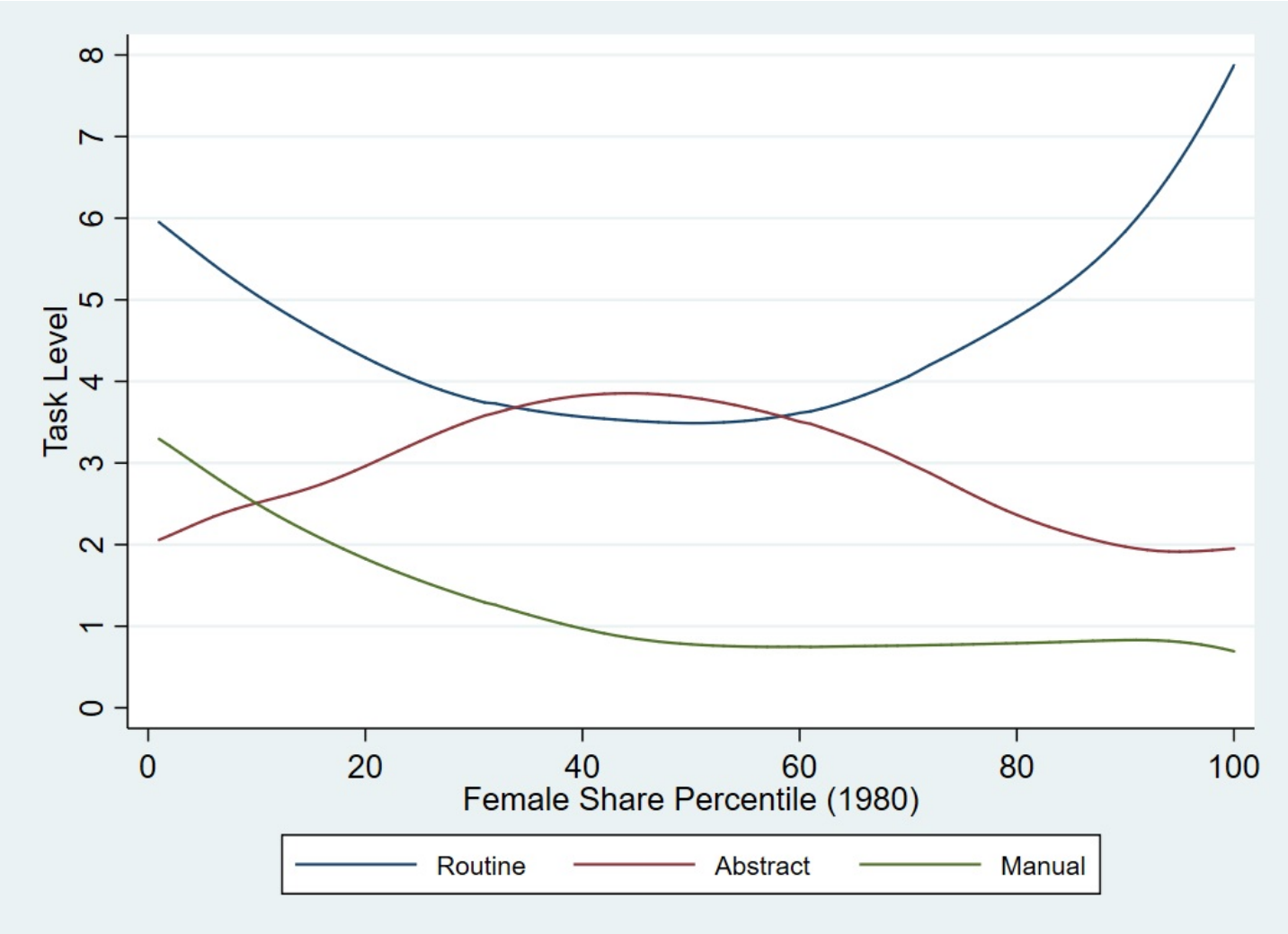
	RTI index	Abstract tasks	Routine tasks	Manual tasks
Managers/prof/tech/finance/public safety	−	+	−	−
Production/craft	+	+	+	−
Transport/construct/mech/mining/farm	−	−	+	+
Machine operators/assemblers	+	−	+	+
Clerical/retail sales	+	−	+	−
Service occupations	−	−	−	+

Notes: The table indicates whether the average task value in occupation group is larger (+) or smaller (−) than the task average across all occupations. Shaded fields indicate the largest task value for each occupation group.

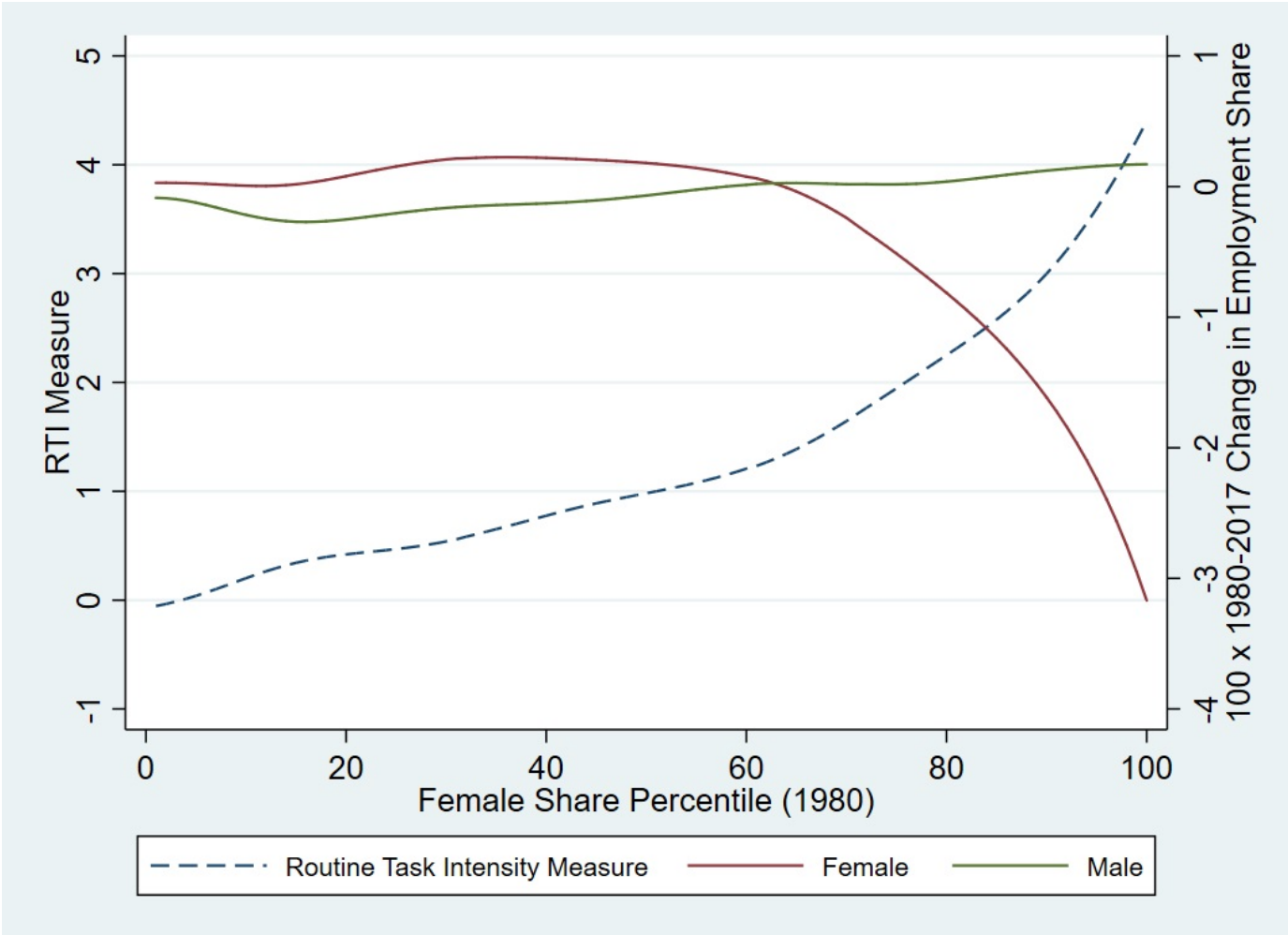
Source: Autor and Dorn (2013)

Four groups: (1) Professional/technical occs, (2) High RTI (production/craft, machine operators/assemblers, clerical/retail), (3) Non-service low RTI (transport/construct/etc.), (4) Service occupations

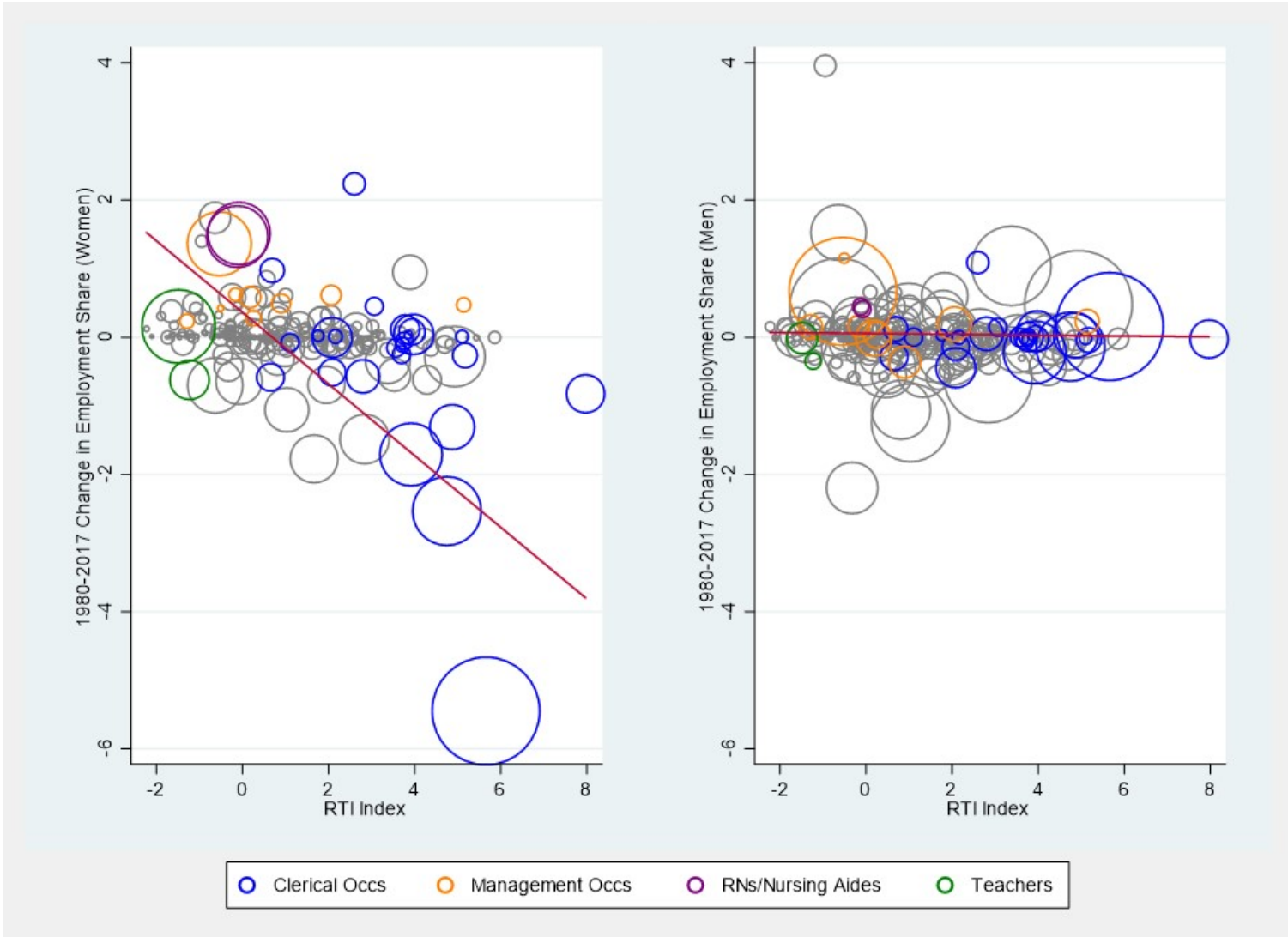
Occupational Tasks by 1980 Female Share Percentile



RTI and Change in Occupation Shares by Female Share Percentile



Change in Employment Share and RTI by Gender



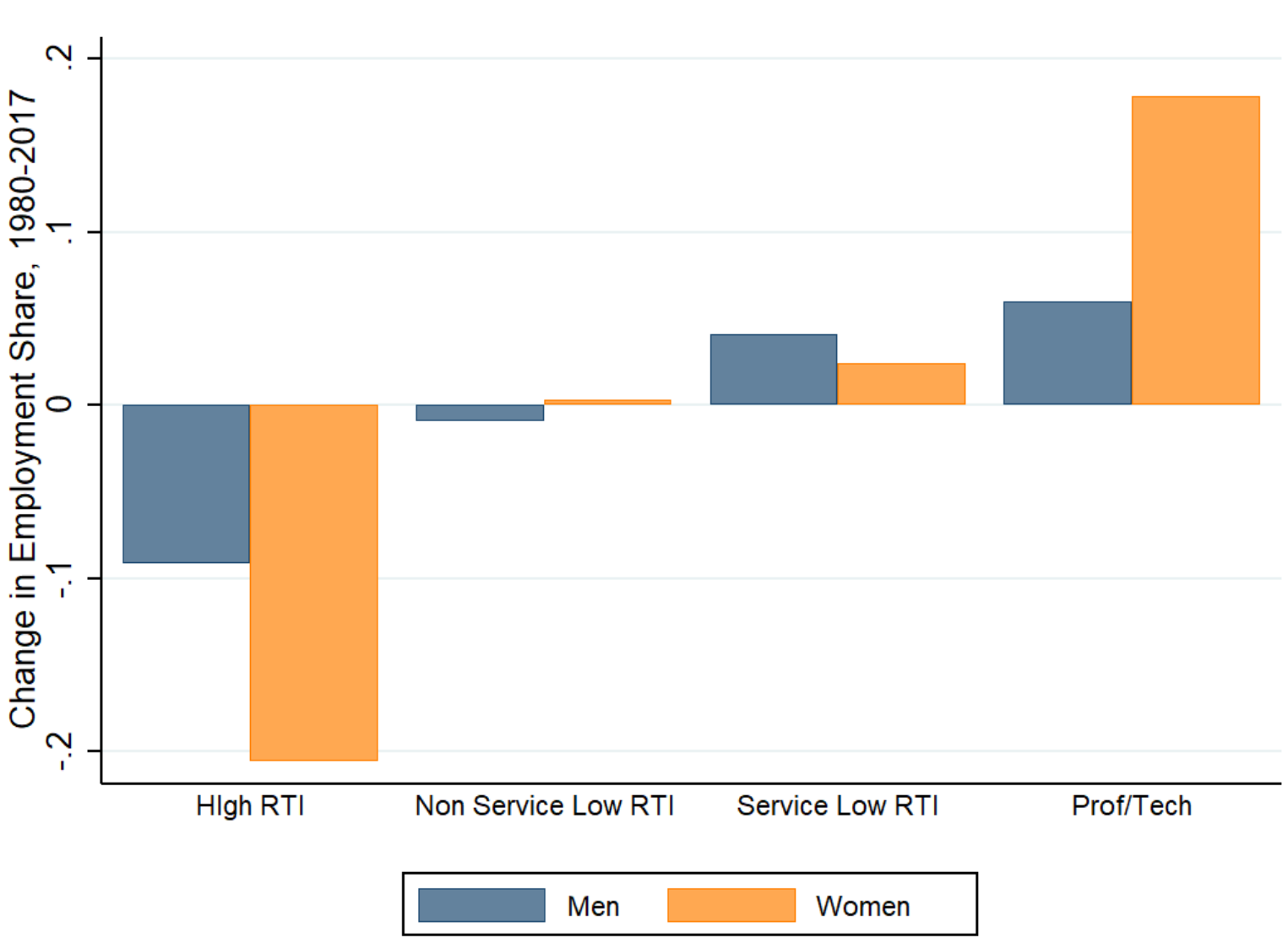
RTI or Female Share?

Dep. Var: 100 x Change in Occupational Share 1980-2017

	Women			Men		
	(1)	(2)	(3)	(4)	(5)	(6)
RTI	-0.507***	-0.433***	-0.142**	-0.022	-0.049	-0.046
	(0.201)	(0.163)	(0.059)	(0.054)	(0.054)	(0.056)
Share Female		-1.523*	-0.134		0.602***	0.666***
		(0.846)	(0.578)		(0.203)	(0.243)
Excluded Occ	None	None	Clerical	None	None	Clerical
No. Obs	308	308	281	309	309	282

Regressions are weighted by the 1980 employment share of each occupation. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Changes in Occupational Distribution by Gender



Summary

- We identify three important facts from our descriptive exercise:
  1. In 1980, a much larger share of women than men were working in occupations with a high risk of automation.
  2. The cross-occupation relationship between risk of automation in 1980 and the change in employment share from 1980 to 2017, though negative for both genders, is much steeper for women.
  3. A relatively higher share of women appear to switch to high-skill occupations as compared to men.

- However, is automation the driving force behind these differential changes?
  - Lots of other changes during this period of time:
    - Large-scale entry of women in the labor market
    - Decline in educational and occupational barriers for women
    - Change in gender norms
  - We therefore turn to cross-commuting zone variation to explore this hypothesis more carefully.

Data II

- 1950 to 2000 U.S. Census and 2010 (2008–2010), 2017 (2015–2017) ACS 3-year aggregates
- Main sample: Native-born workers age 18–64 who are employed in the civilian labor force and who live in their state of birth.
  - Also show results for the full sample, including migrants (both international and internal).
- Local labor markets: Based on 722 Commuting Zones (CZs)
  - Tolbert and Sizer (1996), Autor and Dorn (2013)
  - Clusters of counties with strong commuting ties within CZs; covers U.S. mainland (both rural and city areas)

Cross-Commuting Zone Analysis

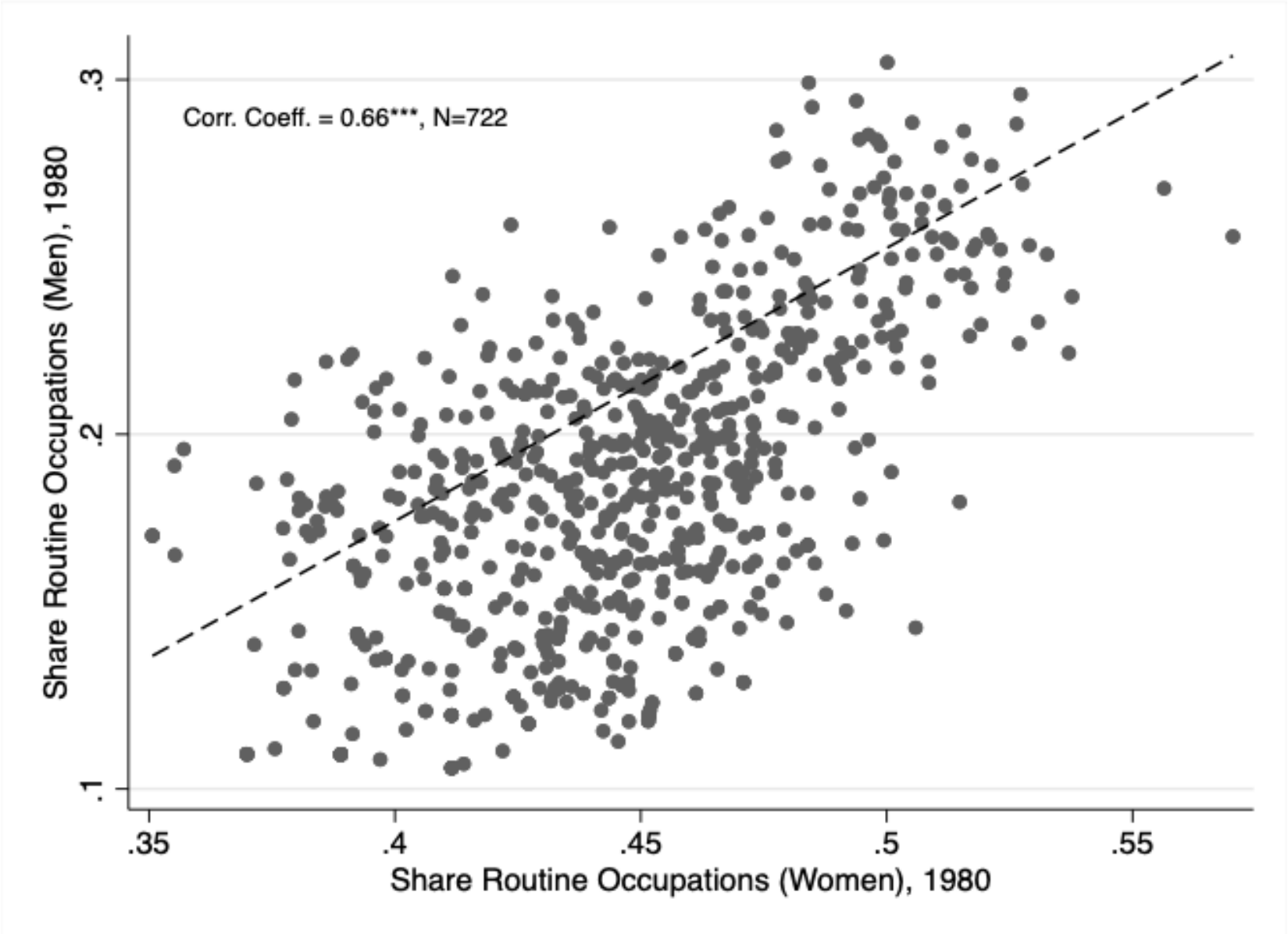
- To measure routine task intensity at the geographic level by gender:
  - We use the RTI index to identify the set of occupations that are in the top employment-weighted third of routine task-intensity. These occupations can be thought as routine-intensive occupations.
  - Then, for each commuting zone j and gender g, we compute a a routine employment share measure, RSH_{jgt}:

$$RSH_{jgt} = \left(\sum_{k=1}^{K} L_{jkgt} \times 1 \left[RTI_k > RTI^{y,P66} \right] \right) \left(\sum_{k=1}^{K} L_{jkgt} \right)^{-1} \quad (1)$$

  where L_{jkgt} is the employment in occupation k of individuals of gender g in commuting zone j at time t, and $1[\cdot]$ takes the value of one if the occupation is routine-intensive.

▸ summary statistics

Cross-Commuting Zone Variation in RSH



Empirical Specification I

$$\Delta_{t-(t-1)} Y_j^g = \delta_t^g + \beta^g RSH_{jt-1}^g + X'_{jt-1}\alpha^g + \gamma_s^g + \epsilon_{jt}^g \qquad (2)$$

- $\Delta_{t-(t-1)} Y_j^g$ is the change in outcome Y in CZ j, for gender $g = \{M, F\}$, between years t and $t-1$
- RSH_{jt-1^g} is the CZ's start-of-period routine-share for gender g
- X'_{jt-1} represents a set of control variables measured at the CZ level at the start of the period in t
- δ_t and γ_s are time period and state FE
- Four time periods: 1980-1990, 1990-2000, 2000-2010, 2010-2017
- Standard errors are clustered on state and observations are weighted by start-of-period CZ share of national population

Empirical Specification II

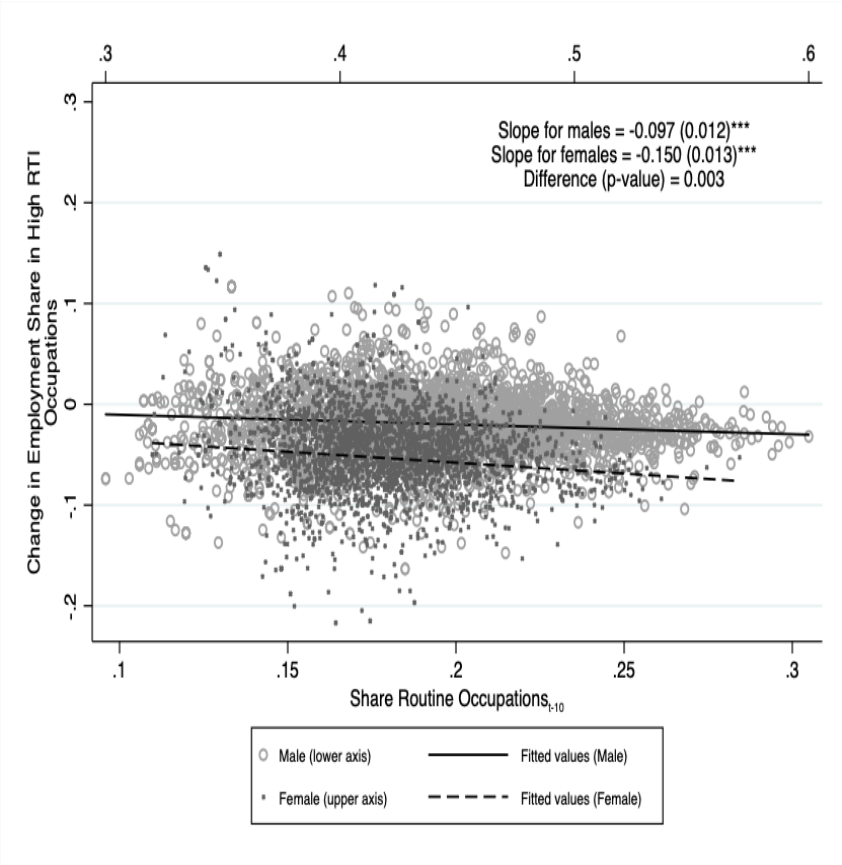
- To study the effect of automation on occupational segregation and the college gap, we modify our estimating equation slightly:

$$\Delta_{t-(t-1)} Y_j = \delta_t + \beta RSH_{jt-1} + X'_{jt-1}\alpha + \gamma_s + \epsilon_{jt} \tag{3}$$

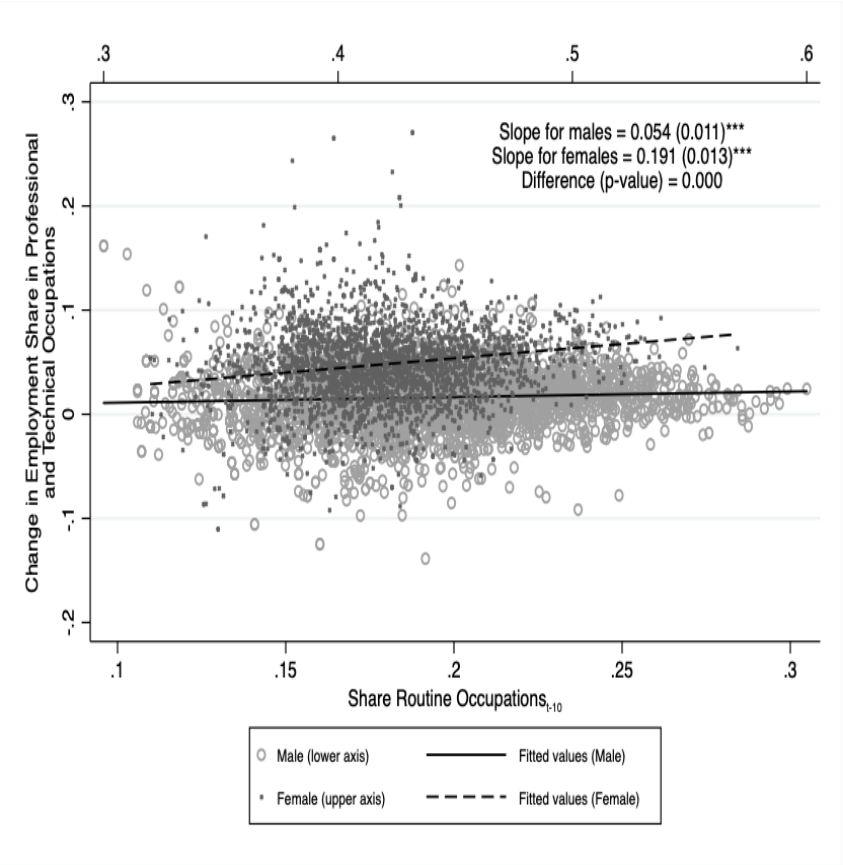
- Here, the main outcomes are the change in the Duncan Segregation Index (1955) and the college gap (men-women).
  - Seg. index ranges between 0 and 1; indicates the proportion of women or men that would need to change occupations for the occ distribution of men and women to be the same.
  - For the college gap, focus on men and women between the ages of 25 to 34.
- Our main explanatory variable is the start-of-period RSH for men and women combined.

Graphical Evidence: Occupational Distribution by Gender

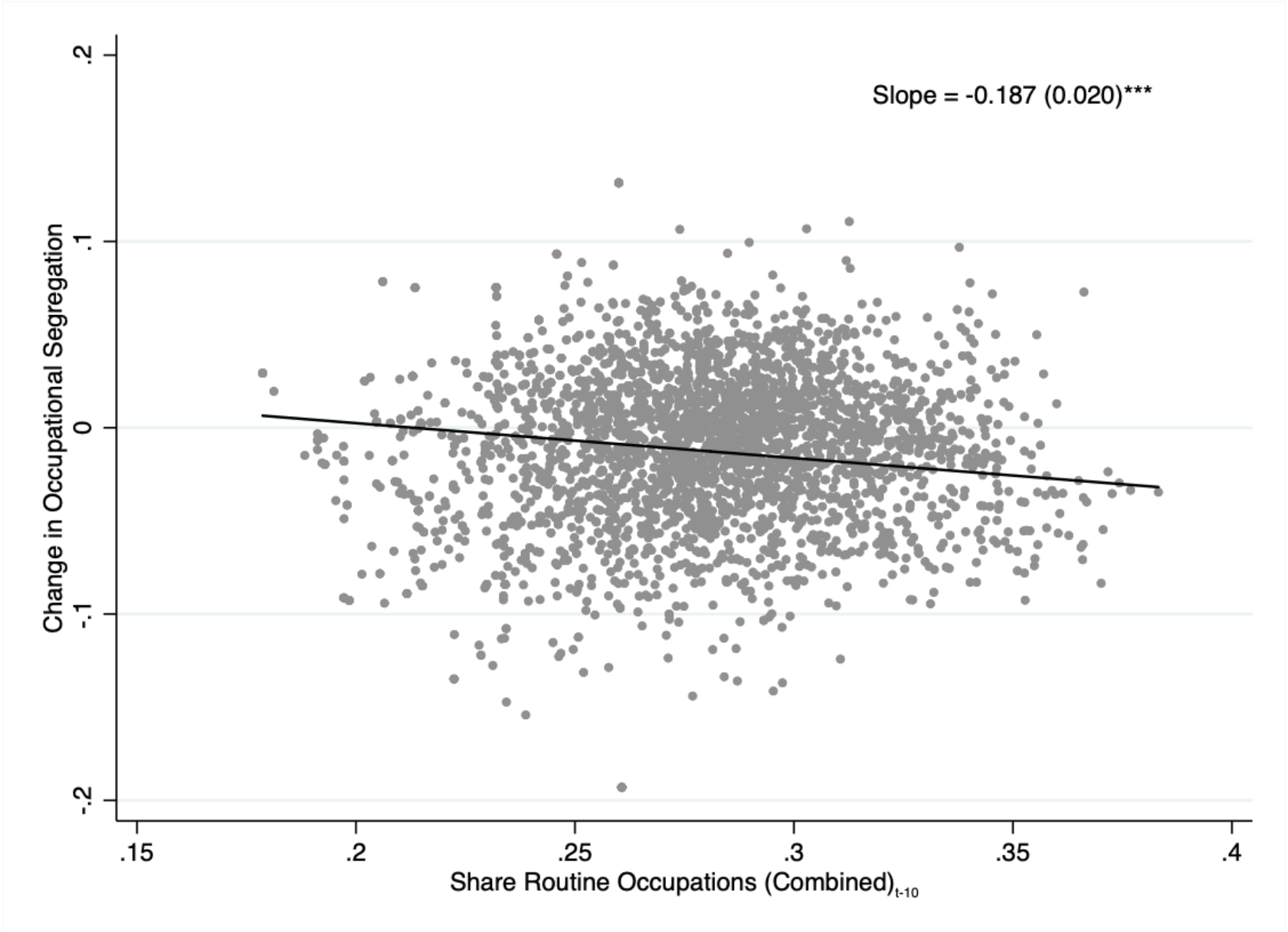
High RTI Occupations



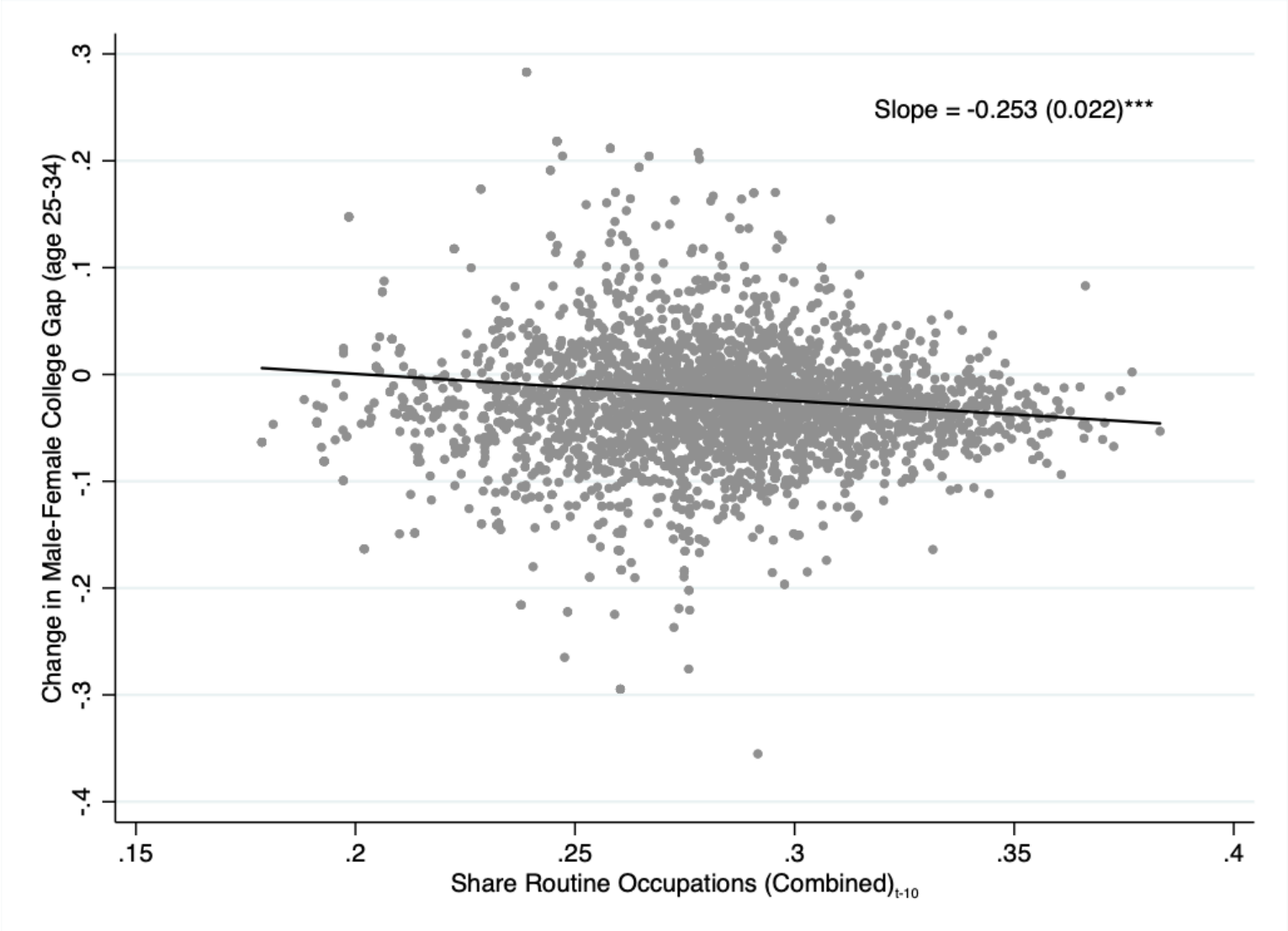
Professional and Technical Occupations



Graphical Evidence: Occupational Segregation



Graphical Evidence: Male-Female College Gap



Controls

- Supply-side
  - Returns in the labor market:
    - LFP participation of college-educated married women
    - Share of low-skilled immigrants (Cortes and Pan, 2019)
  - Returns in the marriage market:
    - Marriage gap between college and non-college women
    - Family income gap between college and non-college women
- Demand-side
  - Lower barriers to entry for women in top occupations:
    - Female share in top 10% highest paying occupations
  - Marketization and structural transformation:
    - Service sector share of employment (Ngai and Petrongolo, 2017)
  - Growth in the healthcare sector:
    - Share of the population aged 65+
- Capture other factors that may explain differences across CZs in changes in occupational segregation and skill investments.
  - Included as either start-of-period levels or contemporaneous changes.
  - Prefer using levels, as changes could themselves be a result of automation; but, results also robust to using changes.

Instrument

- To address the potential endogeneity of routine employment share in a CZ, we use an instrument developed by Autor and Dorn (2013).
  - Isolate the long-run, quasi-fixed component of RSH in a CZ.
  - Predict component of RSH attributable to a CZ's local industry mix in 1950 and the occ structure of industries *nationally* in 1950.

$$\hat{RSH}_j^g = \sum_{i=1}^{I} E_{i,j,1950}^g \times R_{i,-s,1950}^g \tag{4}$$

    - $E_{i,j,1950}^g$ is the employment share of industry i in commuting zone j for gender g in 1950.
    - $R_{i,-s,1950}^g$ is the routine occupation share among workers of gender g in industry i in 1950 in all US states except the state s that includes commuting zone j.
  - Instrument for the share of routine occupations in specification (2) using interactions between the 1950 industry-mix instrument (i.e. $\hat{RSH}_j^g$) and time dummies.

First Stage

	Dep. Variable: Routine Occupation Share (RSH)					
	Men	Women	Men	Women	Men	Women
Predicted Routine Share x 1980	0.764***	0.269***	0.672***	0.241***	0.766***	0.256***
	(0.053)	(0.036)	(0.045)	(0.030)	(0.055)	(0.035)
Predicted Routine Share x 1990	0.585***	0.110***	0.459***	0.078***	0.580***	0.124***
	(0.059)	(0.024)	(0.045)	(0.024)	(0.057)	(0.023)
Predicted Routine Share x 2000	0.552***	0.034	0.439***	0.015	0.546***	0.042**
	(0.059)	(0.022)	(0.052)	(0.021)	(0.059)	(0.020)
Predicted Routine Share x 2010	0.538***	0.034	0.411***	0.018	0.527***	0.042*
	(0.065)	(0.023)	(0.058)	(0.022)	(0.062)	(0.022)
F-stat on instruments	116	27	108	18	116	32
Controls	None		Levels		Changes	
R-squared	0.722	0.713	0.758	0.759	0.723	0.731
Observations	2,880					

▸ combined RSH

Changes in the Occupational Distribution

	Dep. Variable: 10 x Annual Change in Employment Share in Specific Occupation Groups							
	OLS		2SLS					
Sample:	Born and residing in the same state						All	
	Men	Women	Men	Women	Men	Women	Men	Women
	A. High RTI Occupations							
Routine Occ Share$_{-1}$	-0.069***	-0.381***	-0.075***	-0.534***	-0.153***	-0.822***	-0.205***	-0.691***
	(0.020)	(0.040)	(0.024)	(0.127)	(0.041)	(0.122)	(0.036)	(0.096)
	B. Professional and Technical Occupations							
Routine Occ Share$_{-1}$	0.066***	0.301***	0.105***	0.502***	0.132***	0.712***	0.170***	0.597***
	(0.022)	(0.034)	(0.021)	(0.131)	(0.039)	(0.140)	(0.035)	(0.090)
	C. Non-Service Low RTI Occupations							
Routine Occ Share$_{-1}$	0.015	0.000	-0.044***	0.005	0.023	0.016	0.020	0.004
	(0.014)	(0.004)	(0.017)	(0.011)	(0.025)	(0.015)	(0.026)	(0.014)
	D. Service Low-RTI Occupations							
Routine Occ Share$_{-1}$	-0.011	0.080***	0.015	0.027	-0.002	0.093	0.016	0.090*
	(0.010)	(0.021)	(0.012)	(0.069)	(0.017)	(0.070)	(0.012)	(0.053)
Controls	None		None		Levels		Levels	
Observations	2,880							

▸ by education ▸ routine share combined

Changes in Occupational Segregation

	Dep. Var: Change in Segregation Index			
	OLS	2SLS		
	Born and residing in the same state			All
Routine Occupation Share (combined)$_{-1}$	-0.172***	-0.279***	-0.214***	-0.270***
	[0.024]	(0.029)	(0.048)	(0.026)
Controls	None	None	Levels	Levels
Observations	2,880			

Changes in Occupational Segregation

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	[0.024]	(0.029)	(0.048)	(0.026)
Controls	None	None	Levels	Levels
Observations	2,880			

– The 80th-20th percentile in RSH in 1980 is 0.07. Implies a difference of approx. 1.5pp. per decade decline in occ. segregation in the 80th vs. 20th percentile CZ (relative to a mean decadal change of 1.9pp. over 1980–2017).

Potential Channels

Why were women more able to adapt to the changes?

- More easily increase their human capital:
  - Lower cost of entering college
  - Retrain/upskill (entering nursing at age 40)
- Interpersonal and social skills, combined with analytical skills, complement computers (Deming, 2017)
  - Computarization leads to reallocation of workers into flexible, team-based settings
  - Women have higher social skills

Changes in the College Gap (Men-Women), Age 25-34

	Dep. Var: 10 x Annual Change in the College Gap (Men-Women)			
	OLS	2SLS		
	Born and residing in the same state			All
Routine Occupation Share (combined)$_{-1}$	-0.134***	-0.116***	-0.096**	-0.131***
	(0.020)	(0.025)	(0.041)	(0.032)
Controls	None	None	Levels	Levels
Observations	2,880			

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	OLS	2SLS		
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	(0.020)	(0.025)	(0.041)	(0.032)
Controls	None	None	Levels	Levels
Observations	2,880			

– The 80th-20th percentile in RSH in 1980 is 0.07. Implies a difference of approx. 0.7pp. per decade decline in the college gap in the 80th vs. 20th percentile CZ (relative to a mean decadal change of 2.8pp. over 1980–2017).

Placebo Tests: Effects Prior to 1980?

	1980-2017 Panel			1950-1980 Panel		
	OLS	2SLS		OLS	2SLS	
	A. Dep. Var: Change in Segregation Index					
Routine Occupation Share (combined)$_{-1}$	-0.172***	-0.279***	-0.214***	0.055*	0.084***	0.175***
	(0.024)	(0.029)	(0.048)	(0.033)	(0.032)	(0.042)
	B. Dep. Var: Change in the College Gap (Men-Women)					
Routine Occupation Share (combined)$_{-1}$	-0.134***	-0.116***	-0.096**	0.047*	0.029	0.028
	(0.020)	(0.025)	(0.041)	(0.026)	(0.028)	(0.048)
Controls	None	None	Levels	None	None	Levels
Observations		2,880		1,407	1,407	1,407

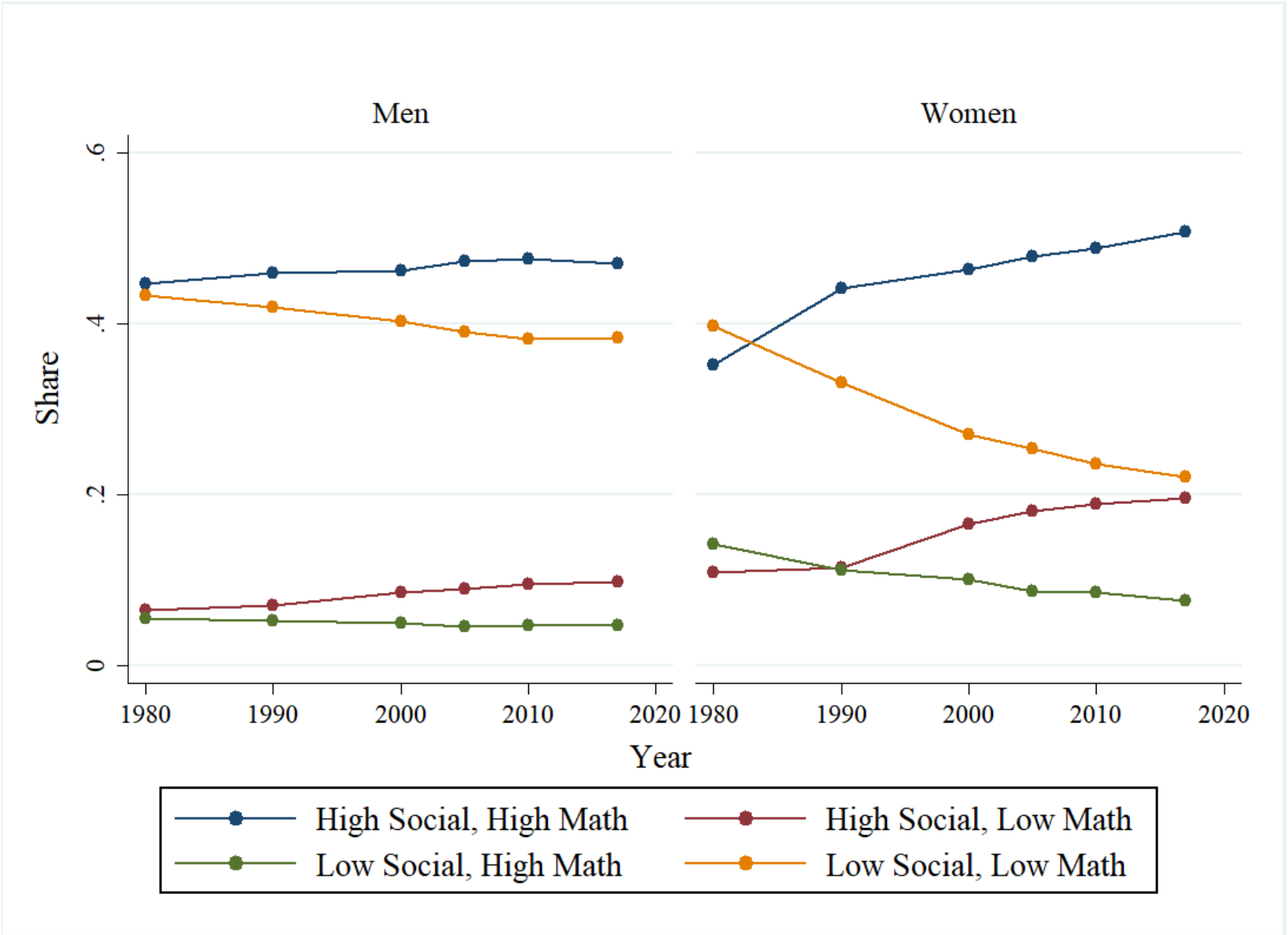
Complementarity Hypothesis

- We explore this hypothesis by:
  - Exploring if local labor markets with higher routine task intensity experienced an increase in share working in social skills intensive occupations, particularly women
  - Following Deming (2017) and looking at changes in shares in four types of occupations:
    - High social, high math
    - High social, low math
    - Low social, high math
    - Low social, low math
  - Defined based on being above/below the median in social skill and nonroutine analytical task intensity as measured in the 1998 O*NET.
- If computerization increases the complementarity between math skills and social skills, we should observe that CZs with higher RSH see a larger expansion in high social, high math occupations.

Examples of Occupations with High and Low Math and Social Skills

Occupations by social and math requirement	
High-Social & High-Math	Managers and administrators
	Production supervisors or foremen
	Primary school teachers
	Retail salespersons and sales clerks
	Sales supervisors and proprietors
High Social & Low Math	Health and nursing aides
	Lawyers and judges
	Stock and inventory clerks
	Fire fighting, fire prevention, and fire inspection occs
	Guards and police, except public service
Low Social & High Math	Bookkeepers and accounting and auditing clerks
	Mathematicians and statisticians
	Production checkers, graders, and sorters in manufacturing
	Physical scientists
	Electricians
Low Social & Low Math	Truck, delivery, and tractor drivers
	Secretaries and stenographers
	Machine operators
	Laborers, freight, stock, and material handlers
	Janitors

Aggregate Trends over Time



Social Skills

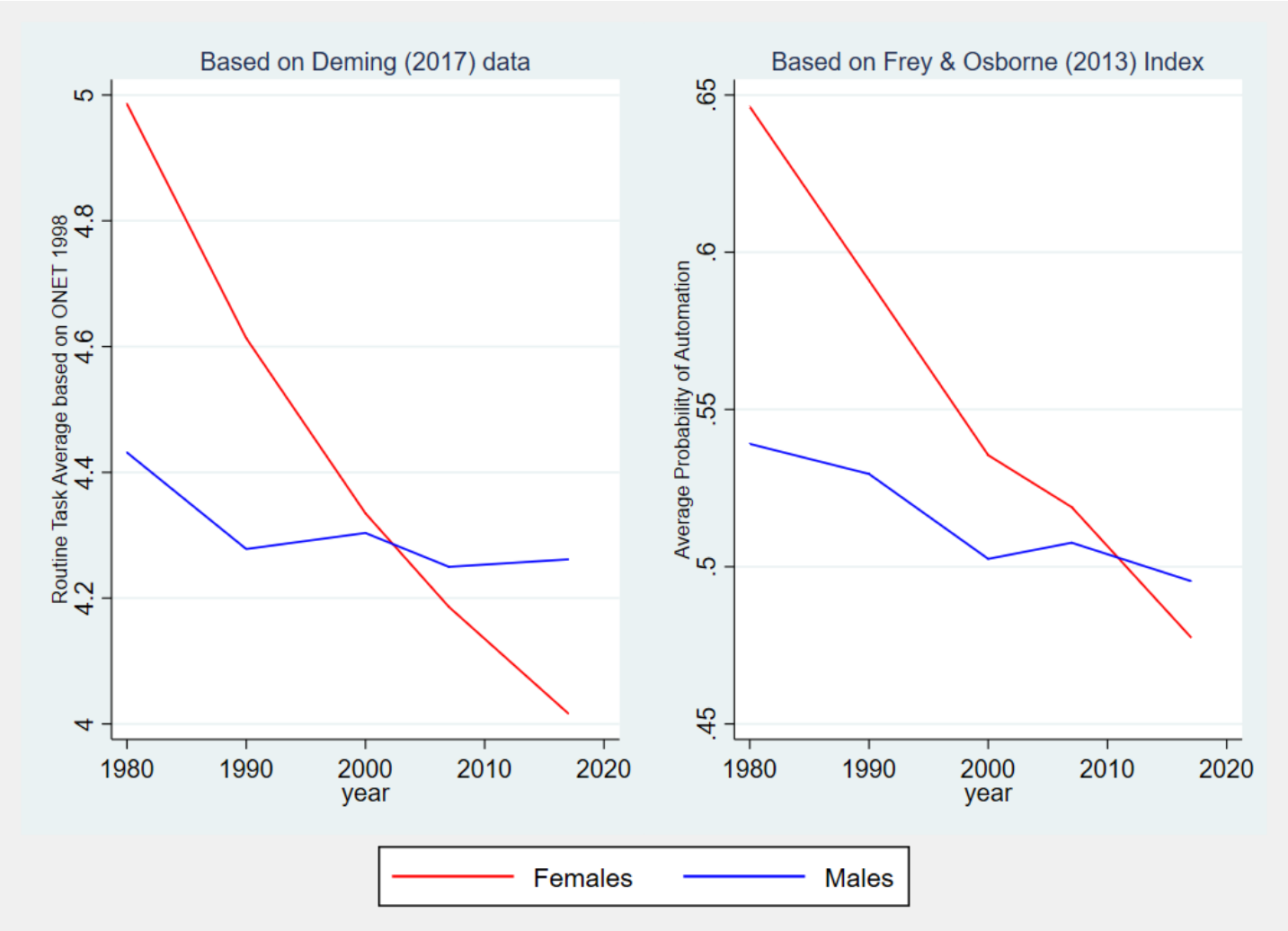
	Dep. Variable: 10 x Annual Change in Employment Share in Specific Occupation Groups							
	OLS		2SLS					
	Born and residing in the same state						All	
	Men	Women	Men	Women	Men	Women	Men	Women
	High Social Skills Occupations (Top Tercile)							
Routine Occ Share$_{-1}$	0.042**	0.251***	0.071***	0.373***	0.090**	0.571***	0.158***	0.427***
	(0.020)	(0.032)	(0.017)	(0.113)	(0.040)	(0.128)	(0.038)	(0.080)
	High Math High Social							
Routine Occ Share$_{-1}$	0.094***	0.287***	0.137***	0.414***	0.236***	0.687***	0.280***	0.535***
	(0.029)	(0.028)	(0.026)	(0.116)	(0.043)	(0.127)	(0.045)	(0.081)
	Low Math High Social							
Routine Occ Share$_{-1}$	-0.006	0.030**	0.012	0.003	-0.018	0.080	-0.004	0.089
	(0.009)	(0.015)	(0.010)	(0.063)	(0.016)	(0.074)	(0.013)	(0.058)
	High Math Low Social							
Routine Occ Share$_{-1}$	-0.042***	-0.132***	-0.055***	-0.275***	-0.061***	-0.323***	-0.070***	-0.210***
	(0.012)	(0.019)	(0.014)	(0.048)	(0.016)	(0.055)	(0.013)	(0.035)
	Low Math Low Social							
Routine Occ Share$_{-1}$	-0.047**	-0.185***	-0.094***	-0.141	-0.156***	-0.444***	-0.206***	-0.414***
	(0.021)	(0.032)	(0.021)	(0.090)	(0.044)	(0.099)	(0.042)	(0.079)
Controls	None		None		Levels		Levels	
Observations	2,880							

Concluding Thoughts

- We provide evidence that automation:
  - Explains part of the changes in the college gender gap
  - Helped reduce occupational segregation.
  - Led to disproportionally more women moving away from routine intensive occupations into professional and technical occupations, in particular, those requiring social skills

- What are the implications of these changes on the risks of future waves of technological change by gender?
  - Reasons to expect that moving forward, automation will pose more of a challenge for men relative to women:
    - Convergence in exposure to routine tasks
    - Women's educational attainment has increasingly outpaced that of men
    - Women have a comparative advantage in interpersonal and social skills

Trends in Risk of Automation - Updated Measures

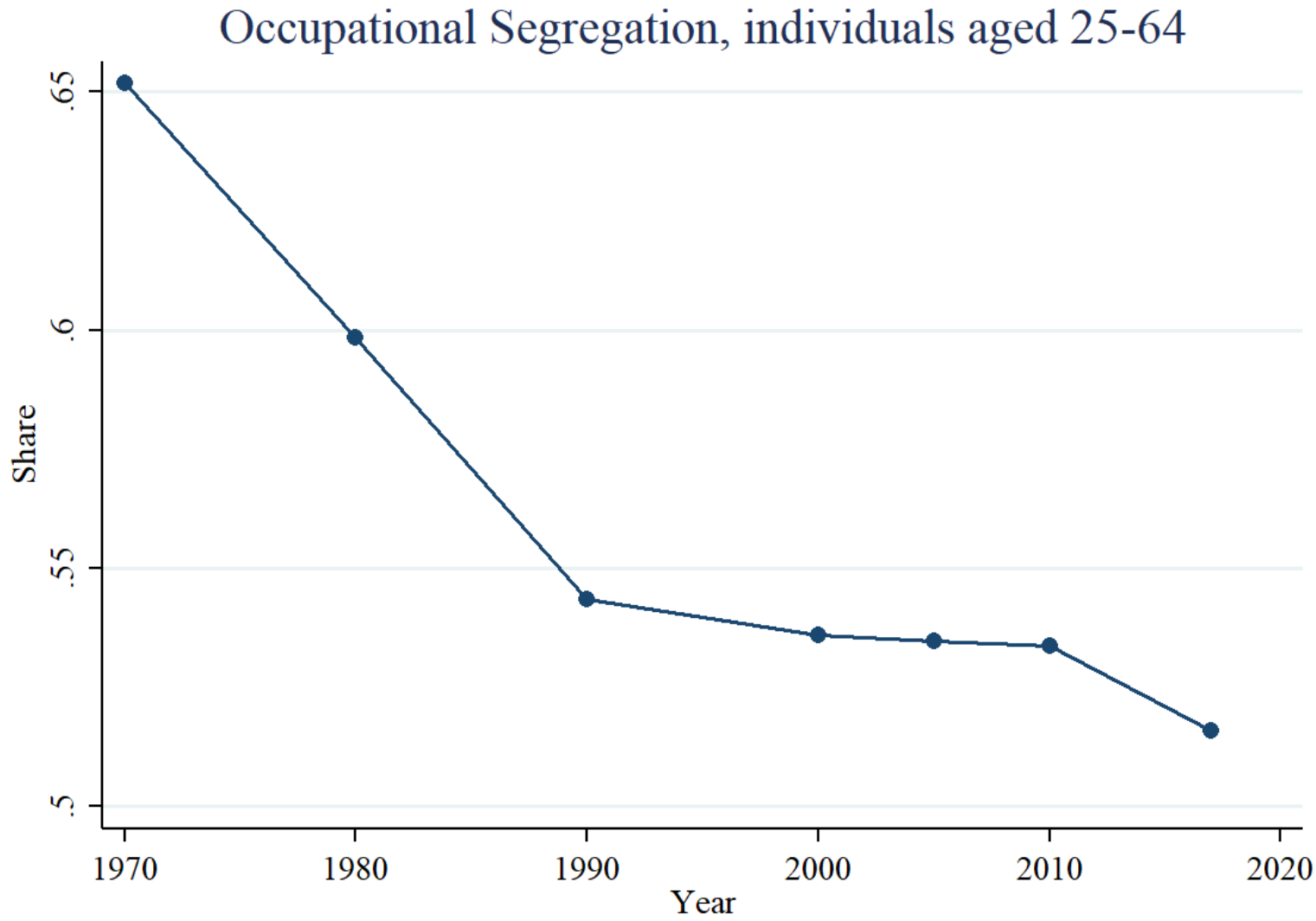


Next Steps

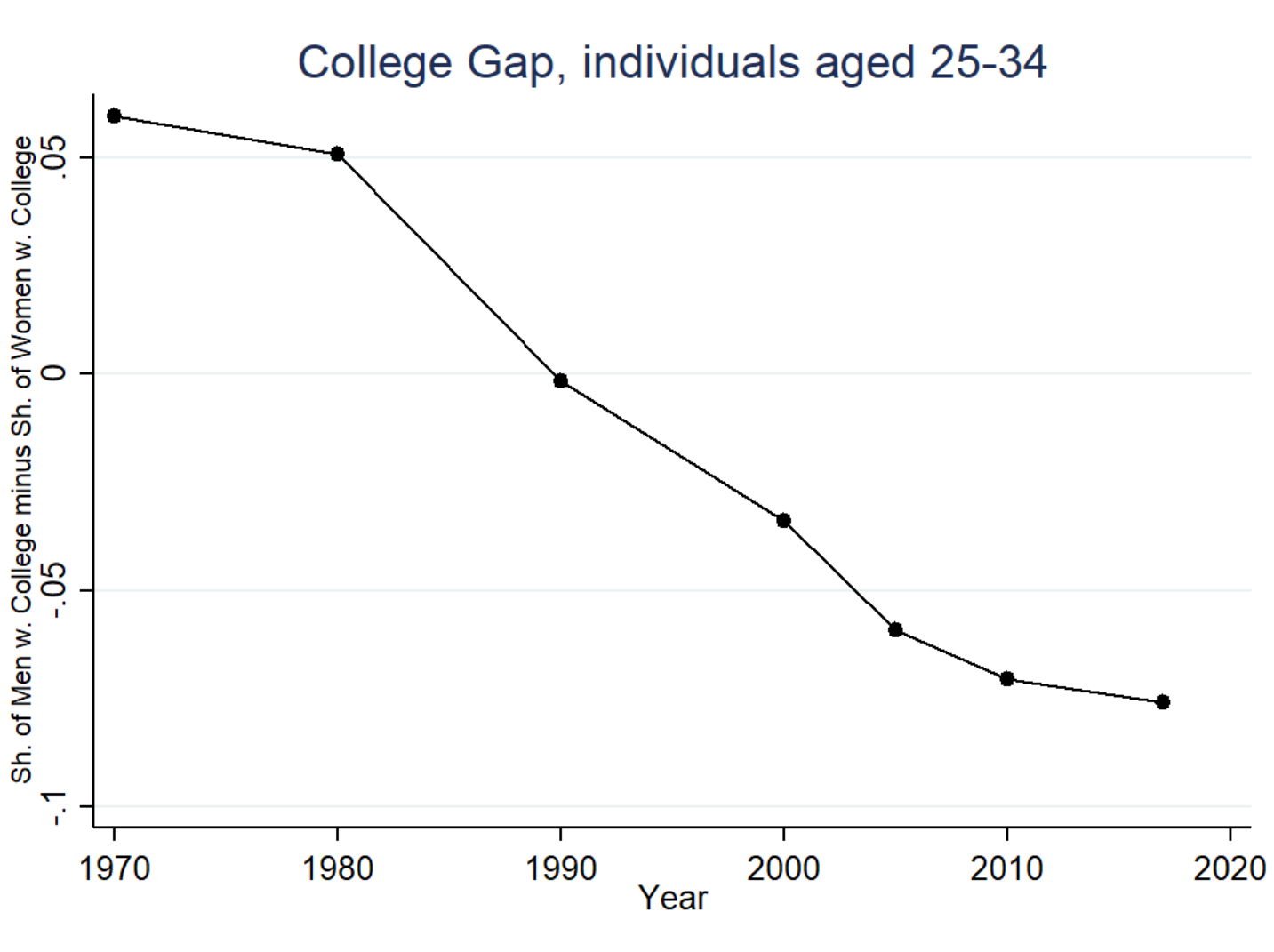
- Robustness of results to alternative specifications of the RTI index and the RSH measure.
- Descriptive analysis of other types of upskilling using longitudinal data.
- Develop a model that allows for gender differences in comparative advantage in social skills and endogenizes the skill investment decisions of men and women.

Labor Force Participation

	Dep. Variable: 10 x Annual Change in LFP			
	OLS	2SLS		
	Born and residing in the same state			All
			Women	
Routine Occupation Share$_{-1}$	-0.122***	0.101	0.005	-0.361***
	(0.035)	(0.109)	(0.102)	(0.061)
			Men	
Routine Occupation Share$_{-1}$	0.044***	0.036**	-0.044	-0.054*
	(0.015)	(0.019)	(0.030)	(0.030)
Controls	None	None	Levels	Levels
Observations	2,888			


Occupational Segregation, individuals aged 25-64
Share
.5
.55
.6
.65
1970
1980
1990
2000
2010
2020
Year

back


College Gap, individuals aged 25-34
Sh. of Men w. College minus Sh. of Women w. College
.05
0
-.05
-.1
1970
1980
1990
2000
2010
2020
Year

back

Summary Statistics

	Mean	SD	p20	p80
Routine Occ Share -1 :				
Men	0.232	0.034	0.201	0.259
Women	0.435	0.040	0.400	0.469
Combined	0.313	0.030	0.287	0.340
Decadal Change:				
Occupational Segregation Index	-0.019	0.033		
College Gap (Men-Women)	-0.028	0.037		
		Men		
Decadal Change in Employment Share in:				
High RTI Occs	-0.023	0.022		
Professional & Technical Occs	0.018	0.021		
Non-Service Low RTI Occs	-0.006	0.020		
Service Low-RTI Occs	0.010	0.012		
		Women		
High RTI Occs	-0.056	0.029		
Professional & Technical Occs	0.051	0.029		
Non-Service Low RTI Occs	0.001	0.005		
Service Low-RTI Occs	0.004	0.019		

back

First Stage for Combined RSH

	Dep. Variable: Routine Occupation Share (RSH), Combined		
Predicted Routine Share x 1980	0.716***	0.666***	0.691***
	(0.040)	(0.042)	(0.041)
Predicted Routine Share x 1990	0.488***	0.405***	0.482***
	(0.034)	(0.042)	(0.034)
Predicted Routine Share x 2000	0.378***	0.336***	0.367***
	(0.035)	(0.047)	(0.040)
Predicted Routine Share x 2010	0.329***	0.273***	0.329***
	(0.036)	(0.051)	(0.039)
F-stat on instruments			
Controls	None	Levels	Levels
R-squared	0.689	0.724	0.697
Observations		2,880	

back

Δ in the Occupational Distribution – College

	Dep. Variable: 10 x Annual Change in Employment Share in Specific Occupation Groups, College-Educated Workers							
	OLS		2SLS					
Sample:	Born and residing in the same state						All	
	Men	Women	Men	Women	Men	Women	Men	Women
	A. High RTI Occupations							
Routine Occ Share$_{-1}$	-0.010	-0.187***	-0.023	-0.463***	0.028	-0.406**	0.053	-0.283**
	(0.029)	(0.027)	(0.029)	(0.153)	(0.038)	(0.168)	(0.044)	(0.130)
	B. Professional and Technical Occupations							
Routine Occ Share$_{-1}$	0.024	0.209***	0.064**	0.508***	-0.005	0.479***	-0.047	0.351**
	(0.029)	(0.030)	(0.031)	(0.161)	(0.041)	(0.179)	(0.045)	(0.139)
	C. Non-Service Low RTI Occupations							
Routine Occ Share$_{-1}$	-0.005	-0.004	-0.020**	0.003	0.006	0.008	0.019	0.000
	(0.010)	(0.003)	(0.010)	(0.009)	(0.019)	(0.013)	(0.018)	(0.009)
	D. Service Low-RTI Occupations							
Routine Occ Share$_{-1}$	-0.009	-0.018	-0.021**	-0.049	-0.029**	-0.081*	-0.025**	-0.068*
	(0.009)	(0.015)	(0.010)	(0.039)	(0.012)	(0.046)	(0.011)	(0.039)
Controls	None		None		Levels		Levels	
Observations	2,880							

back

Δ in the Occupational Distribution – Non-College

	Dep. Variable: 10 x Annual Change in Employment Share in Specific Occupation Groups, Non-College Educated Workers							
	OLS		2SLS					
Sample:	Born and residing in the same state						All	
	Men	Women	Men	Women	Men	Women	Men	Women
	A. High RTI Occupations							
Routine Occ Share$_{-1}$	-0.047*	-0.257***	-0.037	-0.433***	-0.194***	-0.690***	-0.267***	-0.518***
	(0.026)	(0.032)	(0.029)	(0.119)	(0.048)	(0.128)	(0.046)	(0.108)
	B. Professional and Technical Occupations							
Routine Occ Share$_{-1}$	-0.024*	0.176***	-0.056***	0.306***	-0.012	0.467***	0.016	0.274***
	(0.013)	(0.028)	(0.012)	(0.087)	(0.019)	(0.101)	(0.020)	(0.053)
	C. Non-Service Low RTI Occupations							
Routine Occ Share$_{-1}$	0.042**	0.015	-0.001	0.051**	0.137***	0.066***	0.108***	0.046**
	(0.018)	(0.010)	(0.019)	(0.025)	(0.036)	(0.026)	(0.035)	(0.018)
	D. Service Low-RTI Occupations							
Routine Occ Share$_{-1}$	0.028	0.066**	0.095***	0.076	0.069**	0.157	0.142***	0.198*
	(0.020)	(0.029)	(0.023)	(0.084)	(0.027)	(0.095)	(0.023)	(0.103)
Controls	None		None		Levels		Levels	
Observations	2,880							

back

Δ in the Occupational Distribution – Routine Occ Share Combined

	Dep. Variable: 10 x Annual Change in Employment Share in Specific Occupation Groups							
	OLS		2SLS					
Sample:	Born and residing in the same state						All	
	Men	Women	Men	Women	Men	Women	Men	Women
	A. High RTI Occupations							
Routine Occ Share Comb-1	-0.059***	-0.338***	-0.083***	-0.334***	-0.144***	-0.456***	-0.179***	-0.432***
	(0.020)	(0.029)	(0.024)	(0.038)	(0.037)	(0.064)	(0.033)	(0.044)
	B. Professional and Technical Occupations							
Routine Occ Share Comb-1	0.083***	0.240***	0.137***	0.262***	0.150***	0.410***	0.154***	0.399***
	(0.020)	(0.021)	(0.019)	(0.029)	(0.040)	(0.067)	(0.031)	(0.041)
	C. Non-Service Low RTI Occupations							
Routine Occ Share Comb-1	-0.003	0.007**	-0.066***	0.003	-0.003	0.000	-0.000	-0.002
	(0.017)	(0.003)	(0.019)	(0.003)	(0.029)	(0.005)	(0.030)	(0.004)
	D. Service Low-RTI Occupations							
Routine Occ Share Comb-1	-0.021**	0.090***	0.012	0.069***	-0.004	0.045	0.025	0.035
	(0.009)	(0.019)	(0.016)	(0.026)	(0.022)	(0.030)	(0.015)	(0.025)
Controls	None		None		Levels		Levels	
Observations	2,888							

back