Graduate Labor Economics

Lecture 5: Tasks, Polarization, and the Future of Work

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Today's lecture

- Autor, Levy, and Murnane (2003)
- Labor market polarization
- The future of work

What do computers do?

- SBTC literature: computerization associated w/skill upgrading
- But why? What's the mechanism?
- Autor, Levy, and Murnane (2003): what can computers do?
  - Computers excel at "rapid execution of stored instructions"
  - But can fail dramatically at tasks that cannot be codified
  - Polanyi's paradox: "We can know more than we can tell."
- Shifting locus of technological change
  - ALM period: automated production, bookkeeping, ATMs
  - Today: driverless cars, OCR, facial recognition, translation

Substitution and complementarity

[C]omputer capital **substitutes** *for workers in carrying out a limited and well-defined set of cognitive and manual activities, those that can be accomplished by following explicit rules (what we term "routine tasks") . . .*

[C]omputer capital **complements** *workers in carrying out problem-solving and communication activities ("nonroutine" tasks). . . . Provided that routine and nonroutine tasks are imperfect substitutes, these observations imply measurable changes in the task composition of jobs.*

Task taxonomy

PREDICTIONS OF TASK MODEL FOR THE IMPACT OF COMPUTERIZATION ON FOUR CATEGORIES OF WORKPLACE TASKS

	Routine tasks	Nonroutine tasks
	Analytic and interactive tasks	
Examples	• Record-keeping • Calculation • Repetitive customer service (e.g., bank teller)	• Forming/testing hypotheses • Medical diagnosis • Legal writing • Persuading/selling • Managing others
Computer impact	• Substantial substitution	• Strong complementarities
	Manual tasks	
Examples	• Picking or sorting • Repetitive assembly	• Janitorial services • Truck driving
Computer impact	• Substantial substitution	• Limited opportunities for substitution or complementarity

(Autor et al., 2003, Table 1)

The ALM model: production

- Production is a mix of routine and non-routine tasks

$$Q = (L_R + C)^{1-\beta} L_N^{\beta}$$

where L_R, L_N: human labor, C: computers

- All inputs measured in efficiency units
- Key assumption: C and L_N are *relative complements*
    - Perfect substitution b/w computers and routine labor
    - Unit-elastic substitution b/w computers and non-routine (Cobb-Douglas form is just for tractability)
- Computer capital elastically supplied at rental rate ρ
    - Implies $w_R = \rho$
    - Cheaper computers $\implies$ declines in w_R

The ALM model: occupational choice

- Worker i endowed with efficiencies $\{r_i, n_i\} \in (0,1] \times (0,1]$
- Roy selection: choose routine iff $w_R r_i \geq w_N n_i$
  - Threshold rule: indifferent if $\frac{n_i}{r_i} = \frac{w_R}{w_N}$
  - Generates upward-sloping labor supply in each task
- Cheaper computers reduce routine employment
  - $\rho \downarrow \Longrightarrow$ workers self-select out of routine tasks
  - Likely to occur both within and between occupations
- *Ambiguous* impact on observed routine wages
  - Changes in $\mathbb{E}[w_R r_i]$ depend on who selects out
  - Sorting is by comparative advantage, not absolute
  - General lesson: sweat the selection effect

Industry-level implications

- Challenge: cost of computers is a single time series
- Solution: cross-industry differences in routine intensity
  - Effective way to boost degrees of freedom
  - Alternative: geographic differences (Autor and Dorn 2013)
- Three testable predictions:
  1. Routine-intensive industries adopt computers more heavily
  2. Computer-adopting industries shift away from routine occupations
  3. Computer-adopting occupations shift away from routine tasks

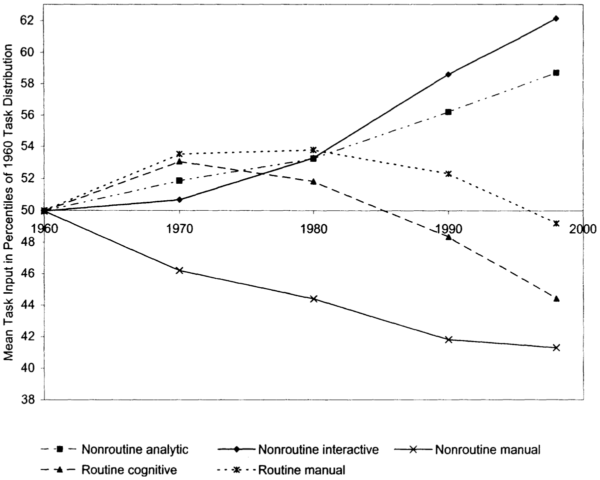
Data

- Task data from Dictionary of Occupational Titles (DOT)
  - 1977 Fourth Edition, 1991 Revised Fourth Edition
  - Occupations scored along 44 dimensions
  - 12,000 detailed job titles
- Employment counts from Decennial Census and CPS ORGs
  - Census: 1960, 1970, 1980, 1990; CPS: 1980, 1990, 1998
  - Weight everything by hours worked
- Lots of crosswalking (see Appendix + my notes)
  - ∼450 Census Occupation Codes
  - ∼140 Census Industry Codes
- Nice feature: observe task changes w/in + b/w occupations
  - A bit unusual: usually know nothing about w/in occ changes

Five measures of task content

- ALM select five measures on prior grounds:
  - Non-routine interactive: "direction, control, and planning"
  - Non-routine analytic: "GED-MATH"
  - Routine cognitive: "set limits, tolerances, or standards"
  - Routine manual: "finger dexterity"
  - Non-routine manual: "eye-hand-foot coordination"
- Embarrassment of riches: are these the right measures?
  - Variable choices may influence results
  - Discretion can invite bias
  - Later literature largely follows ALM conventions
- Verify robustness to other variable choices (using PCA)
- No natural scaling $\implies$ convert to "centiles" of 1960 distribution

Evolution of the aggregate task structure, 1960–1998

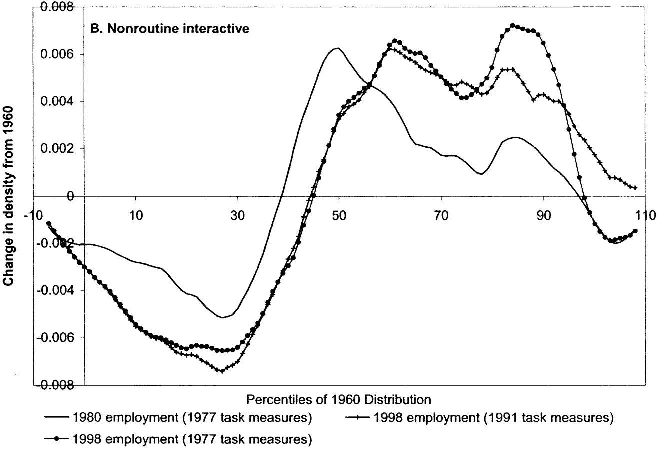


(Autor et al., 2003, Figure 1)

Overall trends in task inputs

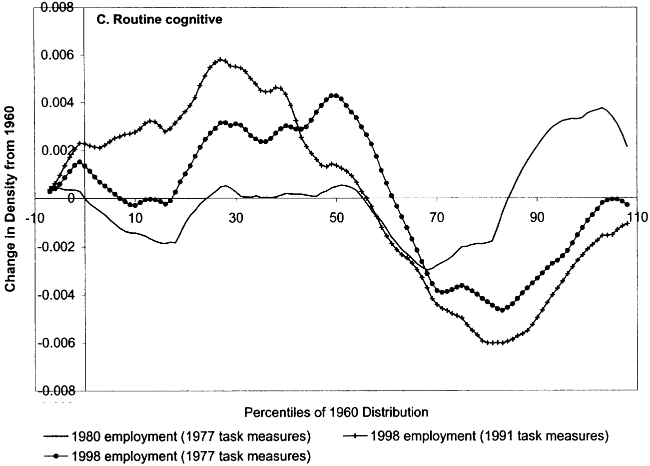
- Secular growth in non-routine interactive/cognitive occupations
  - Already evident in "pre-computer" 1960s
  - Accelerates in subsequent decades, *decelerates* after 2000 (Beaudry, Green, and Sand 2016)
- Declining employment in routine-intensive occupations
  - Reversal of upward trend in the 1960s
  - Declines continue in the 2000s (Autor and Price 2013)
- Secular decline in non-routine manual tasks
  - A little surprising given growth in low-skill services
  - "Neither supportive nor at odds with our model"
- Similar trends among men and among women
- Predominantly driven by within-industry shifts

Rightward shifts in non-routine interactive tasks



(Autor et al., 2003, Figure 2b)

Leftward shifts in routine cognitive tasks



(Autor et al., 2003, Figure 2c)

Computerization and the task structure

- Striking . . . but time-series evidence
- Next: look at industry-level changes in task usage:

$$\Delta T_{jk\tau} = \alpha + \phi \Delta C_j + \varepsilon_{jk\tau}$$

- Estimate separately by decade
  - Static predictor: ΔC_j = 1984–1997 change in computer usage
  - Regard 1960s as pre-treatment (placebo)
  - Expect acceleration as computerization intensifies
- Complement w/contemporaneous data on computer investments

$$\Delta T_{jk\tau} = \alpha + \delta_{70-80} + \delta_{80-90} + \delta_{90-98} + \psi CI_{j\tau} + \theta KI_{j\tau} + \varepsilon_{jk\tau}$$

Computerizing industries shift from routine to non-routine

Computerization and Industry Task Input, 1960–1998
Dependent Variable: 10 × Annual within-Industry Change in Task Input, Measured in Percentiles of 1960 Task Distribution

		1. 1990–1998	2. 1980–1990	3. 1970–1980	4. 1960–1970
A. Δ Nonroutine analytic	Δ Computer use 1984–1997	12.04	14.02	9.11	7.49
		(4.74)	(4.97)	(4.17)	(5.28)
	Intercept	0.07	−0.66	−0.26	−0.55
		(1.00)	(1.03)	(0.86)	(1.05)
	R^2	0.04	0.05	0.03	0.01
	Weighted mean Δ	2.45	2.05	1.48	0.83
B. Δ Nonroutine interactive	Δ Computer use 1984–1997	14.78	17.21	10.81	7.55
		(5.48)	(6.32)	(5.71)	(6.64)
	Intercept	1.02	1.46	2.35	0.10
		(1.15)	(1.31)	(1.17)	(1.32)
	R^2	0.05	0.05	0.03	0.01
	Weighted mean Δ	3.94	4.79	4.42	1.49
C. Δ Routine cognitive	Δ Computer use 1984–1997	−17.57	−13.94	−11.00	−3.90
		(5.54)	(5.72)	(5.40)	(4.48)
	Intercept	−0.11	0.63	1.63	1.78
		(1.17)	(1.19)	(1.11)	(0.89)
	R^2	0.07	0.04	0.03	0.01
	Weighted mean Δ	−3.57	−2.07	−0.47	1.06
D. Δ Routine manual	Δ Computer use 1984–1997	−24.72	−5.94	−6.56	4.15
		(5.77)	(5.64)	(4.84)	(3.50)
	Intercept	1.38	−0.16	2.09	0.85
		(1.22)	(1.17)	(0.99)	(0.70)
	R^2	0.12	0.01	0.01	0.01
	Weighted mean Δ	−3.50	−1.31	0.84	1.62

(Autor et al., 2003, Table 3)

Similar pattern within education groups

Computerization and Industry Task Input 1980–1998:
Overall and by Education Group
Dependent Variable: 10 × Annual Change in Quantiles of Task Measure,
Measured in Percentiles of 1960 Task Distribution

	1. Δ Nonroutine analytic	2. Δ Nonroutine interactive	3. Δ Routine cognitive	4. Δ Routine manual
	A. Aggregate within-industry change			
Δ Computer use	12.95	15.97	−15.84	−14.32
1984–1997	(3.68)	(4.32)	(4.73)	(4.73)
Intercept	−0.33	1.27	0.38	0.54
	(0.77)	(0.90)	(0.99)	(0.99)
Weighted mean task Δ	2.20	4.39	−2.71	−2.25
	B. Within industry: High school dropouts			
Δ Computer use	4.64	11.92	−2.64	−8.85
1984–1997	(6.07)	(8.73)	(7.95)	(6.76)
Intercept	−2.51	−4.39	0.02	1.11
	(1.26)	(1.82)	(1.66)	(1.41)
Weighted mean task Δ	−1.61	−2.07	−0.49	−0.62
	⋮			
	E. Within industry: College graduates			
Δ Computer use	1.61	5.57	−0.78	−4.46
1984–1997	(3.42)	(3.35)	(4.85)	(5.70)
Intercept	0.25	0.10	−0.96	−0.12
	(0.71)	(0.70)	(1.01)	(1.19)
Weighted mean task Δ	0.57	2.22	−1.48	−1.98
	F. Decomposition into within and between education group components			
Explained task Δ	2.52	3.11	−3.09	−2.79
Within educ groups (%)	23.7	77.9	91.7	111.1
Between educ groups (%)	76.3	22.1	8.3	−11.1

(Autor et al., 2003, Table 5)

De-routinization within computerizing occupations

Computerization and Changes in Job Task Content Within Occupations 1977–1991
Dependent Variable: 10 × Annual within-Occupation Change in Quantile of Task Measure, Measured in Percentiles of 1984 Task Distribution

	A. Δ Nonroutine analytic			B. Δ Nonroutine interactive			C. Δ Routine cognitive			D. Δ Routine manual		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Δ Computer use	2.94	3.57	4.02	5.70	5.86	7.08	−18.18	−16.56	−18.48	1.74	0.83	0.37
1984–1997	(1.84)	(1.92)	(2.06)	(1.88)	(1.97)	(2.11)	(3.29)	(3.41)	(3.65)	(2.89)	(3.01)	(3.23)
Δ College grad emp.		−4.79	−4.83		−4.47	−4.58		22.59	22.76		−16.07	−16.03
1984–1997		(5.54)	(5.54)		(5.68)	(5.67)		(9.86)	(9.85)		(8.70)	(8.71)
Δ HS grad emp.		2.83	3.09		−0.19	0.52		16.97	15.86		−10.42	−10.70
1984–1997		(3.78)	(3.81)		(3.88)	(3.90)		(6.73)	(6.77)		(5.94)	(5.99)
Δ Female emp.			−2.37			−6.47			10.14			2.47
1984–1997			(3.94)			(4.03)			(6.99)			(6.19)
Intercept	−0.92	−0.91	−0.95	−0.46	−0.42	−0.52	0.56	0.14	0.30	0.42	0.70	0.74
	(0.40)	(0.41)	(0.41)	(0.41)	(0.42)	(0.42)	(0.71)	(0.72)	(0.73)	(0.63)	(0.64)	(0.64)
R^2	0.01	0.01	0.01	0.02	0.02	0.03	0.06	0.08	0.08	0.00	0.01	0.01
Weighted mean Δ		−0.39			0.58			−2.76			0.74	

(Autor et al., 2003, Table 6)

Implications for relative skill demands

- Do shifts in task demand explain rising demand for college labor?
  - More ambitious ("heroic exercises" come at the end of a paper)
- Posit a "fixed coefficients" mapping from tasks to skills

$$\text{College share}_j = \alpha + \sum_{k=1}^{4} \pi_k \cdot T_j^k + \varepsilon_j$$

- Estimate across industries in midpoint of sample period
- Predicted change in aggregate college share:

$$\Delta \widehat{\text{College share}}_{1970-1988} = \sum_{k=1}^{4} \widehat{\pi}_k \cdot \widehat{\Delta T}^k_{1970-1988}$$

where $\widehat{\Delta T}^k_{1970-1988}$ are computer-induced task shifts

Task shifts can explain much of the shift in skill demands

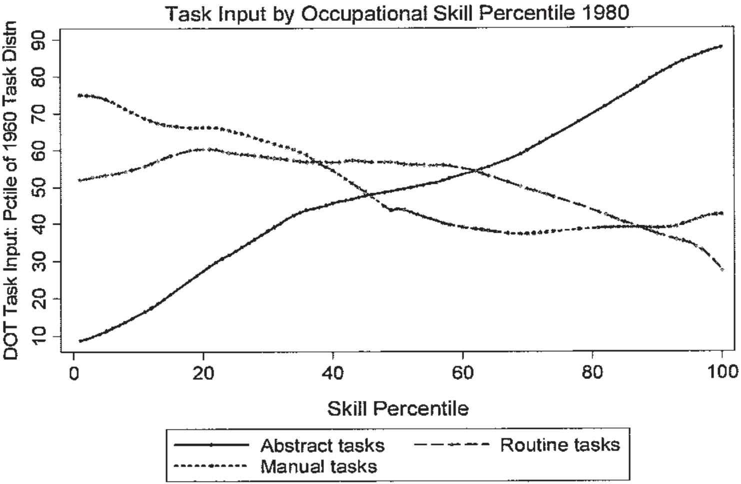
	1. 1970–1980 extensive margin	2. 1980–1990 extensive margin	3. 1990–1998 extensive margin	4. 1970–1998 extensive margin	5. 1980–1998 extensive margin	6. 1980–1998 intensive margin	7. 1980–1998 extensive + intensive
	E. Estimated log demand shifts for college-equivalent/noncollege-equivalent labor 1970–1998 (100 × annual log changes)						
	Using constant-elasticity of substitution model to estimate changes in college demand						
$\sigma = 0.0$	4.99	2.53	2.25	3.33			2.41
$\sigma = 1.4$	3.95	4.65	2.76	3.86			3.81
$\sigma = 2.0$	3.50	5.56	2.98	4.09			4.41
	Using task model to predict changes in college demand						
Total task Δ (panel C)	1.23	1.29	1.43	1.31	1.56	−0.06	1.51
Predicted by computerization (panel D)	0.64	0.70	0.98	0.76	1.39	0.91	2.29

(Autor et al., 2003, Table 7)

The polarization of the labor market

- Related phenomenon: labor market polarization
  - Hollowing-out of middle-paying occupations
  - Non-monotonic changes in wage structure
- One leading explanation: routine-biased technical change
- Likely augmented by globalization (Ebenstein et al., 2014)
  - Import competition from low-wage countries
  - Offshoring of production tasks

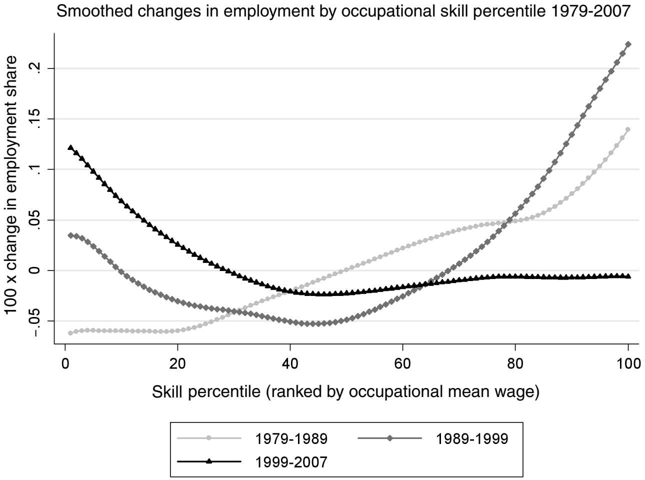
Routine tasks were once prevalent in middle-paying jobs



(Autor et al., 2008, Figure 10)

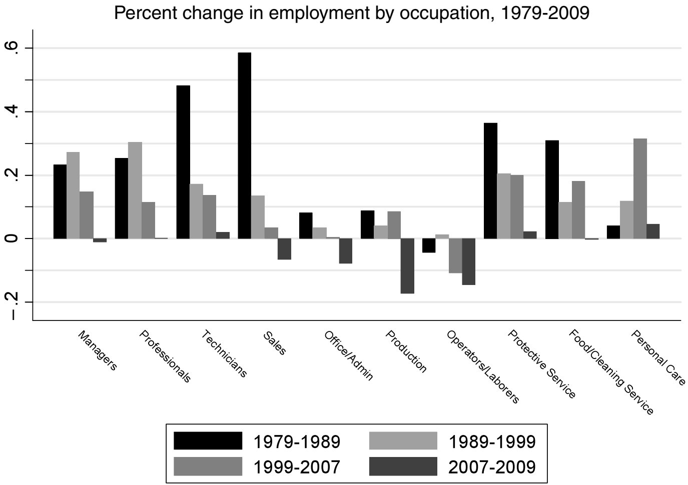
The hollowing-out of middle-paying jobs

(See Hunt and Nunn 2019 for a critique of this occupation-based approach)



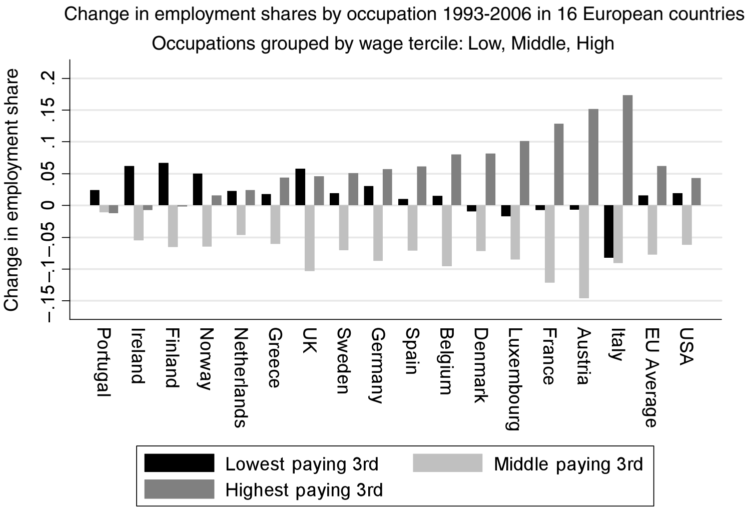
(Acemoglu and Autor, 2011, Figure 10)

Occupational polarization in the United States



(Acemoglu and Autor, 2011, Figure 12)

Occupational polarization throughout Europe



(Acemoglu and Autor, 2011, Figure 11; adapted from Goos et al. 2009)

Wage polarization in the 1990s United States

(Acemoglu and Autor, 2011, Figure 9a)

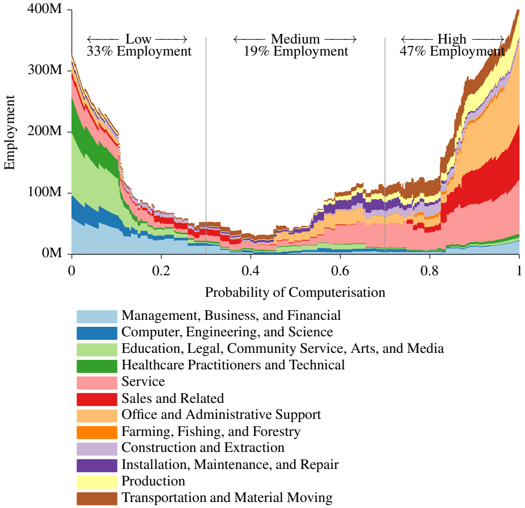
The future of work

- Lots of debate about AI-induced job losses
  - Machine learning (ML), advanced robotics
- Hard to predict the future: easier to predict the past!
- One approach: Frey and Osborne (2017)
  - Hand-code 70 occupations' susceptibility to automation
  - Bottlenecks: perception, creativity, social intelligence
  - Use ML techniques to extrapolate to remaining occupations
- Attention-getting conclusion:

  According to our estimate, 47% of total US employment is in the high risk category, meaning that associated occupations are potentially automatable over some unspecified number of years, perhaps a decade or two.

Frey and Osborne (2017)

(Nifty data visualization. Note the clever color cues: green jobs safe, red jobs at risk.)

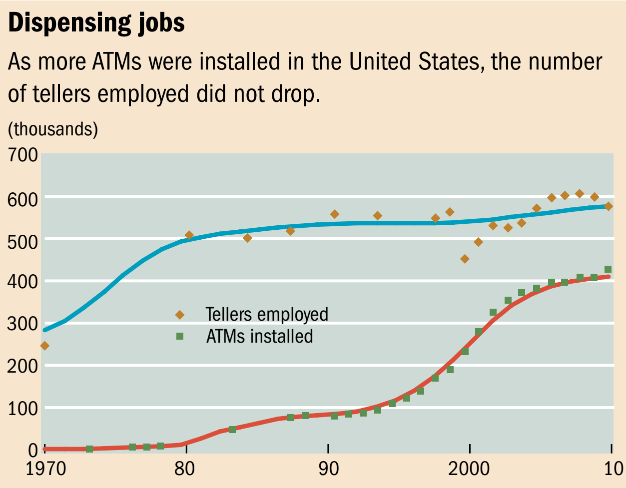


(Frey and Osborne, 2017, Figure 3)

The end of work?

- Are we on the brink of mass technological unemployment?
  - Similar angst throughout history (e.g., Luddites)
- Maybe—but don't fall prey to the "lump of labor" fallacy!
  - Scale effects within industries
  - Demand effects between industries
- Plus: not all *non*-employment is *un*employment
  - A world without work is a wealthy world (Keynes 1930)
  - But big concerns about distribution
  - See Autor (*JEP* 2015)

Cautionary tale: scale effects in bank branching



(Bessen, 2015, Chart 1)

Concluding thoughts

- Task approach increasingly popular—why?
  - Occupations matter, but there are tons of them
  - Tasks offer dimension reduction
  - Tight links to theory
- Lots of fruitful angles
  - Rising returns to social skills (Deming 2017)
  - New job titles (Lin 2011; Autor and Salomons, in prep.)
- Challenges:
  - Time-consistent measures of job characteristics
  - Time-consistent occupational/industry codes
  - Potential cherry-picking of measures