Graduate Labor Economics

Lecture 4: Skill-Biased Technical Change

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Where we are

- Canonical model suggests skill-biased demand shifts
  - Rising skill premium despite rising skill supplies
- But where do they come from?
  - Changes in product demand?
  - Changes in production technology?
- Today: evidence of *skill-biased technical change* (SBTC)
- SBTC is at the heart of many ongoing debates
  - Global rise in income inequality
  - Productivity renaissance/slowdown
  - Mass technological unemployment

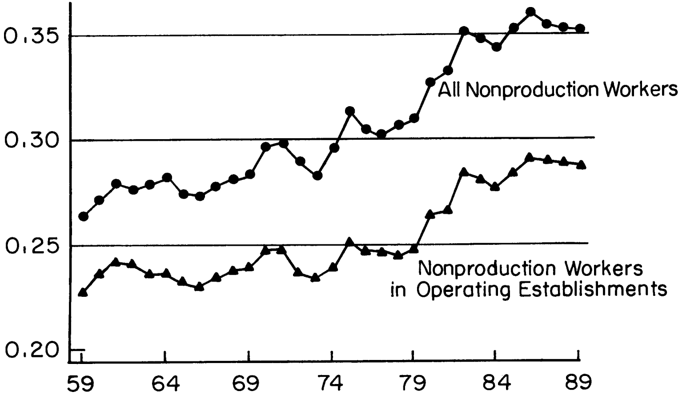
Today's class

- Berman, Bound, and Griliches (1994)
  - Skill-upgrading within manufacturing
  - Between-sector vs. within-sector
  - Indirect evidence of SBTC
- Akerman, Gaardner, and Mogstad (2015)
  - Labor market impacts of broadband rollout
  - Credible identification, terrific data
  - Direct evidence of SBTC

Berman, Bound, and Griliches (1994): data

- Data from the Annual Survey of Manufactures (ASM)
  - Plant-level survey drawn from Census of Manufactures
  - Aggregated to the 4-digit industry level (450 industries)
  - Inputs (labor, capital, materials) and output (sales, value added)
- Today called "NBER-CES Manufacturing Industry Database"
  - Public-use and easy to use: `http://www.nber.org/nberces/`
- Two occupational categories:
  - Production: "fabricating, processing, assembling, inspecting"
  - Non-production: "supervision . . . , installation and servicing of own product, sales, delivery, professional, technological, administrative"
- For each category, observe employment and wage bill

Rising non-production share of manufacturing employment



(Berman et al., 1994, Figure 1)

Skill-upgrading?

- Is the non-production share a valid measure of skill?
    - Subjective assessment of the tasks performed
    - Non-production wages > production wages
    - Non-production share in ASM $\approx$ white-collar share in CPS
- Unlike education, directly manipulable by employers
    - Workers choose how much education to acquire ...
    - ... but employers decide which tasks to assign to workers
- Non-production share likely understates demand shift
    - Rising employment share *despite rising relative cost*
    - Skill-upgrading may also occur *within each category*
- More inclusive measure: non-production share of wage bill

Non-production share tracks white-collar share

Occupational Distributions within Manufacturing by Year

	1973	1979	1987
Total nonproduction	28.3%	30.9%	35.4%
Percent in central offices	17.3%	19.7%	18.4%
White-collar	28.6%	31.9%	37.2%
Manager	27.0	27.0	29.4
Professional	18.8	19.9	21.5
Technician	8.7	9.0	9.0
Sales worker	7.3	7.5	8.8
Clerical worker	38.1	36.6	31.4
Subtotal	100.0	100.0	100.0
Blue-collar	71.4%	68.1%	62.8%
Craft	24.4	25.7	30.3
Operative	62.3	61.6	57.6
Laborer	9.8	9.5	9.0
Service worker	3.0	2.8	2.6
Agricultural labor	0.5	0.5	0.6
Subtotal	100.0	100.0	100.0

Source. Annual Survey of Manufacturing and CPS, May 1973, Outgoing Rotations, 1979 and 1987.

(Berman et al., 1994, Table 1)

Skill-upgrading occurs *within* each "collar" too

OCCUPATIONAL DISTRIBUTIONS WITHIN MANUFACTURING BY YEAR

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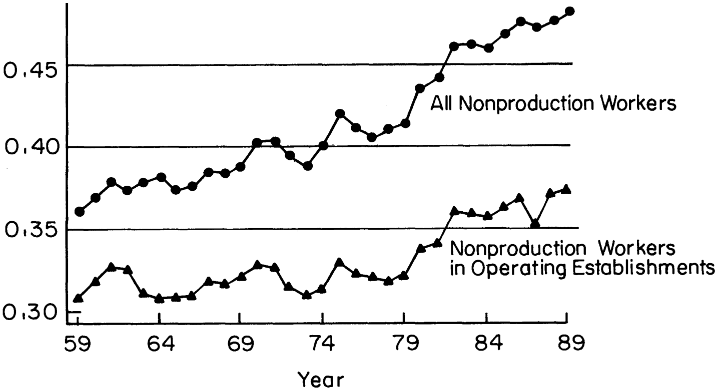
Source. Annual Survey of Manufacturing and CPS, May 1973, Outgoing Rotations, 1979 and 1987.

(Berman et al., 1994, Table 1)

Non-production share of wage bill rises just as much



(Berman et al., 1994, Figure 2)

Three candidate explanations

1. Skill-biased/"labor-saving" technical change
    - Fast TFP growth during the 1980s
    - Growth in R&D and high-tech capital
    - Case-studies linking technology adoption to skill-upgrading
2. Growing openness of the US economy
    - High-skill exports, low-skill imports
    - Outsourcing of production tasks
3. Growth in military spending ("Reagan buildup")
    - High-tech weapons, high-skill workers
    - Quite specific to the 1980s

The logic of the between/within decomposition

- Fix ideas: J industries with Cobb-Douglas production

$$Y_j = N_j^{\beta_j} P_j^{1-\beta_j}$$

  where β_j = non-production share of wage bill

- Two ways to increase non-production share:
  - Shifts towards industries with high β_j
  - Increases in the β_j's themselves

- Decompose changes into between-/within-sector terms
  - Trade, defense $\implies$ between-sector shifts
  - Technology $\implies$ within-sector shifts

Notation (different from BBG)

- J manufacturing industries observed in $t = 0$, $t = 1$
  - $\lambda_{jt} \equiv$ industry j's share of mfg emp
  - $s_{jt} \equiv$ non-production share of ind j emp
  - $s_t \equiv$ non-production share of mfg emp
- Identity: $s_t \equiv \sum_j \lambda_{jt} s_{jt}$
- Goal: decompose $\Delta s \equiv s_1 - s_0$
  - Between component: growth in skill-intensive sectors
  - Within component: skill-upgrading within industries

Deriving the decomposition: one possibility

- Basic approach: add/subtract, then rearrange

$$
\begin{aligned}
\Delta s &= \sum_j \lambda_{j1} s_{j1} - \sum_j \lambda_{j0} s_{j0} \\
&= \sum_j \lambda_{j1} s_{j1} - \sum_j \lambda_{j0} s_{j1} + \sum_j \lambda_{j0} s_{j1} - \sum_j \lambda_{j0} s_{j0} \\
&= \sum_j (\lambda_{j1} - \lambda_{j0}) s_{j1} + \sum_j \lambda_{j0} (s_{j1} - s_{j0}) \\
&= \underbrace{\sum_j \Delta\lambda_j s_{j1}}_{\text{between}} + \underbrace{\sum_j \lambda_{j0} \Delta s_j}_{\text{within}}
\end{aligned}
$$

- Close analogy to Oaxaca-Blinder decompositions

Decompositions like this are not unique

- Issue: decomposition is *order-dependent*
  - "Between" uses $t = 1$ shares, "within" uses $t = 0$ shares
- Alternative expressions:
  - $\Delta s = \sum_j \Delta\lambda_j s_{j0} + \sum_j \lambda_{j1} \Delta s_j$
  - $\Delta s = \sum_j \Delta\lambda_j s_{j0} + \sum_j \lambda_{j0} \Delta s_j + \sum_j \Delta\lambda_j \Delta s_j$
- BBG use a symmetric expression:
  - Start with $\Delta s = \sum_j \lambda_{j1} s_{j1} - \sum_j \lambda_{j0} s_{j0}$
  - Add/subtract $\frac{1}{2}\left(\sum_j \lambda_{j0} s_{j1} + \sum_j \lambda_{j1} s_{j0}\right)$
- Result: $\Delta s = \underbrace{\sum_j \Delta\lambda_j \bar{s}_j}_{\text{between}} + \underbrace{\sum_j \bar{\lambda}_j \Delta s_j}_{\text{within}}$ where $\bar{x}_j \equiv \frac{1}{2}(x_{j1} + x_{j0})$

Rise in skill-intensity driven by *within* component

INDUSTRY/SECTOR DECOMPOSITIONS OF THE RISE IN THE SHARE OF NONPRODUCTION WORKERS

	Employment		Wage bill	
	Between	Within	Between	Within
		1959–1973		
Imports	0.007	−0.001	0.005	−0.001
Exports	0.010	0.002	0.012	0.003
Domestic consumption	−0.026	0.076	−0.035	0.067
	−0.009	0.078	−0.018	0.069
Total		0.069		0.051
		1973–1979		
Imports	0.001	−0.006	−0.007	−0.002
Exports	0.021	0.007	0.028	0.004
Domestic consumption	0.089	0.186	0.064	0.206
	0.112	0.187	0.085	0.208
Total		0.299		0.293
		1979–1987		
Defense	0.072	0.014	0.101	0.004
Imports	0.029	−0.002	−0.024	−0.006
Exports	0.019	0.014	0.035	0.014
Domestic comsumption	0.044	0.361	0.193	0.456
	0.165	0.387	0.306	0.468
Total		0.552		0.774

Note. A calculation for the defense sector is possible only for the 1979–1987 period. Its contribution in earlier periods is included in domestic consumption. All calculations have been annualized.

(Berman et al., 1994, Table 4)

Unpacking things further

- Premise: product demand $\equiv$ between, SBTC $\equiv$ within
- Is this really a perfect correspondence?
  - Offshoring of production tasks $\implies$ skill shifts w/in industries
  - SBTC lowers unit costs $\implies$ tech-intensive industries expand
- BBG further decompose into trade, defense, residual
  - Trade and defense account for much of the between term ...
  - ... but not much of the within term
- See paper for details

Cautionary note: level of aggregation matters!

- Decomposition results depend on level of aggregation
  - BBG use 4-digit SIC codes (pretty granular)
  - But product mix might still change w/in industries
- Suppose ind j is composed of sub-inds $k \in \{1, \ldots, K_j\}$
  - Let $\mu_{jkt} \equiv k$'s share of ind j emp
  - Then $s_{jt} = \sum_k \mu_{jk} s_{jk}$
- One could further decompose BBG's "within" term

$$\underbrace{\sum_j \overline{\lambda}_j \Delta s_j}_{\text{within}} = \underbrace{\sum_j \overline{\lambda}_j \sum_k \Delta \mu_{jk} \overline{s}_{jk}}_{\text{between sub-inds}} + \underbrace{\sum_j \overline{\lambda}_j \sum_k \overline{\mu}_{jk} \Delta s_{jk}}_{\text{within sub-inds}}$$

- See BBG footnote 6 for related discussion

Skill-upgrading and technology adoption

- Rest of BBG: skill-upgrading correlated with R&D, computers
- Lots of papers showing correlations among
  - Skill-upgrading (education, occupations)
  - Adoption of specific technologies
  - Complementary changes in organizational practices
  - Greater customization of products
- Broader settings: non-manufacturing, other countries
- Current frontier: labor market impacts of robots and AI
- See syllabus for some leading papers

Akerman et al. (2015): SBTC in the internet age

- Question: is high-speed internet skill-biased?
  - Positive: how has broadband affected wage structure?
  - Normative: should gov't invest in broadband access?
- Akerman, Gaardner, and Mogstad (2015)
  - Specific, important technological advance
  - Rich administrative + survey data
  - Plausibly exogenous variation in broadband access

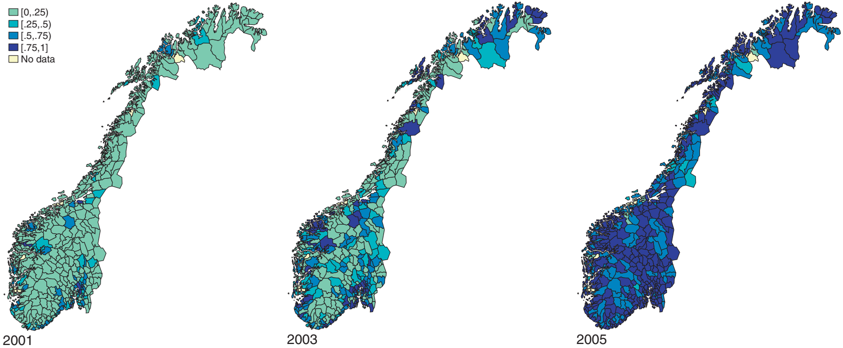
All of the data. All of it.

- Comprehensive data on Norway 2001–2007
- Administrative data on workers and firms
  - Universe of non-financial joint-stock companies
  - Balance sheets: revenue, labor, capital, intermediate inputs
  - Linked to workers: earnings, education, demographics
  - For a large subsample: survey data on hourly wages + occupations
- Admin/survey data on broadband rollout
  - Share of households for whom broadband is available
  - Firm-level broadband adoption (for a random sample)
- Each year: ≈3m workers, 20k firms (2500 w/survey info)
- Geocoded to 428 municipalities

Policy variation

- Institutional backdrop: National Broadband Policy
  - Goal: nationwide broadband access at uniform pricing
  - Means: infrastructure investments, local gov't mandates
  - Carried out by state-owned monopoly (Telenor)
- Key to identification: geographic variation in timing of rollout
  - Bottleneck: installation of local access points
  - Determinants of timing: topography, road network

Broadband access across Norwegian municipalities



(Akerman et al., 2015, Figure 1)

Reduced-form specification: intent-to-treat (ITT)

- How does broadband *availability* affect workers/firms?
- For worker or firm i in municipality m in year t:

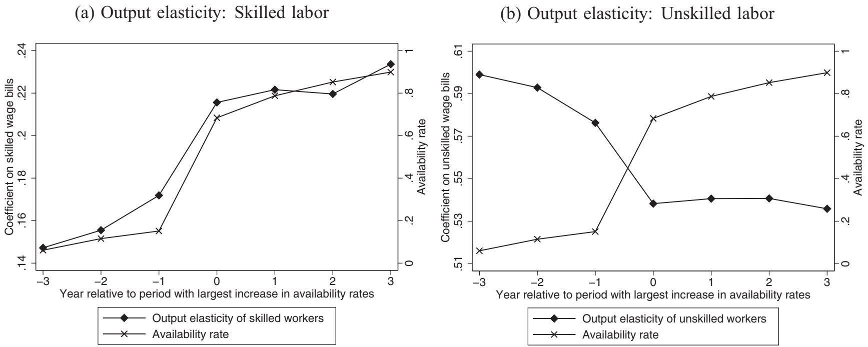
$$y_{imt} = x'_{imt}\delta_0 + z_{mt}x'_{imt}\delta_1 + w'_{imt}\theta + \eta_m + \tau_t + u_{imt}$$

  - z: broadband availability rate
  - Municipality and time fixed effects
  - Cluster on municipality (why?)
- Worker-level regressions:
  - y: employment status or log hourly wage
  - x: education bins, w: sex, experience, and industry(?)
- Firm-level regressions:
  - y: log value added
  - x: capital and labor inputs, w: industry.

Threats to exogeneity

- Concern: is timing of adoption correlated with local trends?
- AGM make several arguments:
  - Determinants of broadband timing change little over time
  - Timing of expansion uncorrelated with baseline observables
  - Results robust to including municipality-specific trends
- Event studies around year of biggest broadband increase

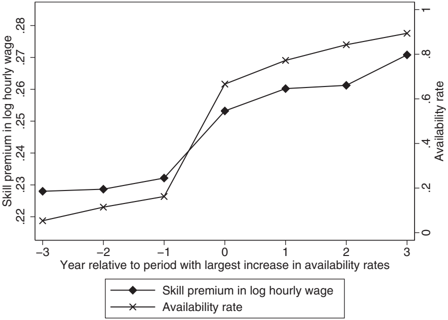
Event study: output elasticities



(Akerman et al., 2015, Figure 2)

Event study: skill premium

(c) Return to Skill: Hourly wage



(Akerman et al., 2015, Figure 2)

Reactions to the event studies

- Discontinuous rise in broadband at date 0 is reassuring ...
  - ... but is it mechanical?
  - Would like to see this explored formally
  - The jumpier the variation, the more credible this design
- Raw data suggest secular trends in output elasticities
  - Regression models will control for time/municipality FEs
  - But adding these controls doesn't seem to kill the pretrends
  - A little disconcerting ... but will survive lots of spec checks
- Unbalanced samples: driven by composition bias?
  - Balanced version very reassuring (Appendix Figure B.2)
- Interpretation: what should we expect here?
  - Short-run effects?
  - Long-run effects?

Reduced-form estimates: wages and employment

Intention-to-Treat Effects on Wages and Employment

Dependent variable	(1) Log hourly wage	(2)	(3) Employment	(4)
	2 skills	3 skills	2 skills	3 skills
Unskilled	2.939***		0.691***	
	(0.00455)		(0.00262)	
Low skilled		2.905***		0.664***
		(0.00431)		(0.00231)
Medium skilled		2.977***		0.731***
		(0.00454)		(0.00288)
Skilled	3.169***	3.171***	0.734***	0.737***
	(0.00420)	(0.00407)	(0.00480)	(0.00477)
Availability ×				
Unskilled	−0.00622		0.000794	
	(0.00455)		(0.00252)	
Low skilled		−0.0108***		−0.00392
		(0.00325)		(0.00244)
Medium skilled		−0.00793		0.00388
		(0.00600)		(0.00281)
Skilled	0.0178**	0.0202***	0.0208**	0.0225**
	(0.00720)	(0.00692)	(0.00920)	(0.00892)
Worker-year observations	8,759,388	8,759,388	20,327,515	20,327,515
		p-values		
Test for no skill bias	.000	.000	.012	.001

(Akerman et al., 2015, Table 3)

Reduced-form estimates: productivity

INTENTION-TO-TREAT EFFECTS ON OUTPUT ELASTICITIES

Dependent variable	(1)	(2)
	Log value added	
	2 skills	3 skills
Intercept	3.880***	4.537***
	(0.0965)	(0.0791)
Log capital	0.100***	0.0981***
	(0.00495)	(0.00490)
Log unskilled	0.576***	
	(0.0116)	
Log low skilled		0.298***
		(0.00804)
Log medium skilled		0.265***
		(0.00684)
Log skilled	0.136***	0.134***
	(0.00678)	(0.00636)
Availability ×		
Intercept	–0.500***	–0.561***
	(0.111)	(0.0976)
Log capital	–0.00169	0.000188
	(0.00750)	(0.00661)
Log unskilled	–0.0226	
	(0.0234)	
Log low skilled		–0.0274***
		(0.00934)
Log medium skilled		0.0179*
		(0.00967)
Log skilled	0.0755***	0.0645***
	(0.0166)	(0.0137)
Firm-year observations	149,676	137,498
	p-values	
Test for no skill bias	.012	.000

(Akerman et al., 2015, Table 4)

Reduced-form estimates: interpretation

- 10 pct. pt. increase in broadband availability:
  - Skilled workers: wages and emp $\uparrow$ 0.2 percent
  - Low-skilled: wages $\downarrow$ 0.1 percent, emp unaffected
- Broadband raises MPL for skilled, lowers MPL for unskilled
- Limited pass-through: output moves more than wages
  - Skilled workers: 20 percent pass-through to wages
  - Suggests firms are earning rents (at least in short run)
- Survives a suite of robustness checks
  - Exclude biggest cities
  - Aggregate to the region level
  - Allow for municipality-specific trends
  - Address endogeneity of inputs (Levinsohn and Petrin 2003)

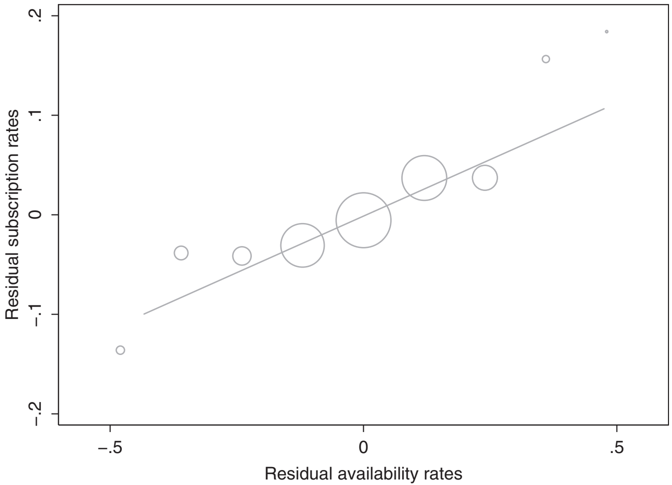
From ITT to TOT

- How does broadband *adoption* affect workers/firms?
- Reduced form hard to interpret: 2SLS rescales the estimates

$$y_{imt} = x'_{imt}\delta_0 + D_{imt}x'_{imt}\delta_1 + w'_{imt}\theta + \eta_m + \tau_t + u_{imt}$$

- Instrument for $D_{imt}x'_{imt}$ using $z_{mt}x'_{imt}$
  - We need a strong first stage
  - We need an exclusion restriction

First stage: broadband access $\Longrightarrow$ broadband adoption



(Akerman et al., 2015, Figure 4)

Which firms adopt broadband?

- Theory predicts non-random adoption decisions
  - Complementary factors
  - Credit constraints?
- Skill-intensive firms are more likely to adopt broadband
  - These firms tend to be bigger or more productive
  - These firms have more workers using PCs
- I think the paper could have done more on this point

Threats to exclusion (i.e., other mechanisms)

1. Broadband access may influence consumer demand
   - Similar findings for the tradable sector
2. Direct impacts on broadband supplying/servicing firms
   - Similar findings if we exclude Telenor and IT consultancies
3. Contemporaneous investments in computers
   - No effect on share of workers using PCs
4. Increased ability to telecommute
   - Maybe, but can't explain decline in low-skilled productivity

Placebo test: no effect on always-takers/never-takers

Placebo Test: Output Elasticities

Dependent variable	(1)	(2)
	Log value added	
	Baseline sample of firms	Always/never taker firms only
Intercept	3.880***	4.388***
	(0.0965)	(0.692)
Log capital	0.100***	0.114***
	(0.00495)	(0.0313)
Log unskilled	0.576***	0.505***
	(0.0116)	(0.0869)
Log skilled	0.136***	0.171***
	(0.00678)	(0.0295)
Availability ×		
Intercept	−0.500***	−0.212
	(0.111)	(0.709)
Log capital	−0.00169	−0.0230
	(0.00750)	(0.0345)
Log unskilled	−0.0226	0.0295
	(0.0234)	(0.0860)
Log skilled	0.0755***	0.00944
	(0.0166)	(0.0278)
Firm-year observations	149,676	2,233

(Akerman et al., 2015, Table 6)

At last: causal impacts on complying firms

Broadband Adoption and Technological Change

Dependent variable	(1)	(2)	(3)	(4)
	Log value added			
	2 skills		3 skills	
	OLS	IV	OLS	IV
Intercept	3.809***	3.751***	4.695***	4.636***
	(0.145)	(0.455)	(0.120)	(0.437)
Log capital	0.0987***	0.0894***	0.110***	0.0980***
	(0.00736)	(0.0227)	(0.00764)	(0.0213)
Log unskilled	0.583***	0.658***		
	(0.0179)	(0.0427)		
Log low skilled			0.307***	0.352***
			(0.0197)	(0.0332)
Log medium skilled			0.228***	0.247***
			(0.0116)	(0.0287)
Log skilled	0.131***	0.0676**	0.129***	0.0844***
	(0.0105)	(0.0293)	(0.0120)	(0.0298)
Broadband ×				
Intercept	−0.618***	−0.765	−0.835***	−0.961**
	(0.181)	(0.550)	(0.173)	(0.468)
Log capital	0.00774	0.0212	−0.00572	0.0125
	(0.0111)	(0.0312)	(0.0109)	(0.0310)
Log unskilled	−0.0297	−0.133**		
	(0.0215)	(0.0604)		
Log low skilled			−0.0340*	−0.100*
			(0.0185)	(0.0512)
Log medium skilled			0.0396***	0.0174
			(0.0135)	(0.0450)
Log skilled	0.0910***	0.195***	0.0851***	0.160***
	(0.0111)	(0.0435)	(0.00756)	(0.0439)
Firm-year observations	16,744	16,744	16,250	16,250
	p-values			
Test for no skill bias	.000	.000	.000	.000

(Akerman et al., 2015, Table 7)

Broadband complements abstract tasks, subs for routine

Wage Regressions with Interactions between Tasks and Broadband Availability

Dependent variable	(1)	(2)	(3)
	Log hourly wage		
		Skill categories	
		2 skill levels	3 skill levels
Abstract	0.371***	0.283***	0.272***
	(0.0142)	(0.0139)	(0.0140)
Routine	−0.0641***	−0.0664***	−0.0700***
	(0.00653)	(0.00573)	(0.00577)
Manual	0.0248***	0.0156**	0.0138*
	(0.00791)	(0.00769)	(0.00740)
Availability × Abstract	0.173***	0.157***	0.157***
	(0.0320)	(0.0298)	(0.0297)
Availability × Routine	−0.0357***	−0.0344***	−0.0338***
	(0.00798)	(0.00766)	(0.00791)
Availability × Manual	0.00200	0.00145	0.00273
	(0.0115)	(0.0107)	(0.0104)
Worker-year observations	4,586,333	4,586,333	4,586,333
Controlling for educational attainment:			
Skill levels	No	Yes	Yes
Availability × Skill levels	No	Yes	Yes
Tests for no task bias:		*p*-values	
Equality of abstract and routine	.000	.000	.000
Equality of abstract and manual	.000	.000	.000
Equality of manual and routine	.041	.040	.036

(Akerman et al., 2015, Table 8)

Wrap-up

- Has SBTC caused skill-biased demand shifts?
- Berman, Bound, and Griliches (1994)
    - Skill-upgrading occurs mostly within (mfg) industries
    - Skill-upgrading correlated with computer investments
- Akerman, Gaardner, and Mogstad (2015)
    - Credible evidence on effects of broadband adoption
    - Boosts MPL of skilled, lowers MPL of unskilled
- Next class: the task structure of employment
  (Autor, Levy, and Murnane 2003)