# Explaining Inequality: The Role of Skills and Tasks

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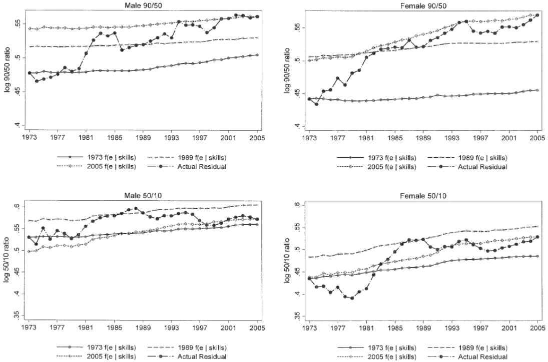
# Rising Within-Group (“Residual”) Inequality

FIGURE 8.—ACTUAL AND COUNTERFACTUAL 90/50 AND 50/10 RESIDUAL HOURLY WAGE INEQUALITY, 1973–2005 (CPS MAY/ORG)




Source: Autor et al. (2008)

- $\Delta$heights (trends): LF composition (unobserved skill “prices”) held constant; “price” effects more pronounced (are these really prices?)
- Assumption: distribution of unobserved skills constant over time (otherwise, just observing increasing inequality in unobserved skill distributions over time)

# How Do We Explain Rising Inequality?

- One explanation: skill-biased technological change (SBTC)
- Another explanation: rise (fall) in demand for complex (routine) tasks
- Report will (sequentially) discuss both

# Baseline Skills Model: Setup

- Katz and Murphy (1992): "canonical" high (H) vs. low (L)-skilled worker model
- Key feature: labor-augmenting technologies ($A_h$, $A_l$)
- Production function:

$$Y(t) = A_t[(A_l(t)L(t))^\rho + (A_h(t)H(t))^\rho]^{1/\rho}]$$

- Profit maximization yields relative demand for skills:

$$\frac{w_H}{w_L} = \left(\frac{A_h}{A_l}\right)^{(\sigma-1)/\sigma} \left(\frac{H}{L}^{-1/\sigma}\right)$$

- How inequality responds to technological change depends on $\sigma$:

$$\frac{\partial\left(\frac{w_H}{w_L}\right)}{\partial\left(\frac{A_h}{A_l}\right)} = \frac{\sigma - 1}{\sigma}$$

# Baseline Skills Model: Results

- Katz and Murphy (1992) first to estimate:

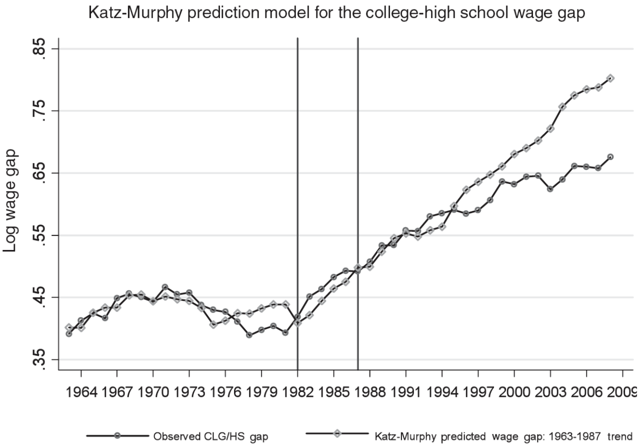
$$\ln \frac{w_H(t)}{w_L(t)} = (\sigma - 1)/\sigma \ln\left(\frac{A_h(t)}{A_l(t)}\right) - 1/\sigma \ln\left(\frac{H(t)}{L(t)}\right) + \varepsilon_t$$

- Results:

$$\ln \frac{w_H(t)}{w_L(t)} = 0.33(0.01) * t - 0.71(15) \ln\left(\frac{H(t)}{L(t)}\right) + C$$

- Conclusion: SBTC (increase in $A_h$) increases inequality (CES $> 1$, since $\hat{\sigma} = 1.41$)

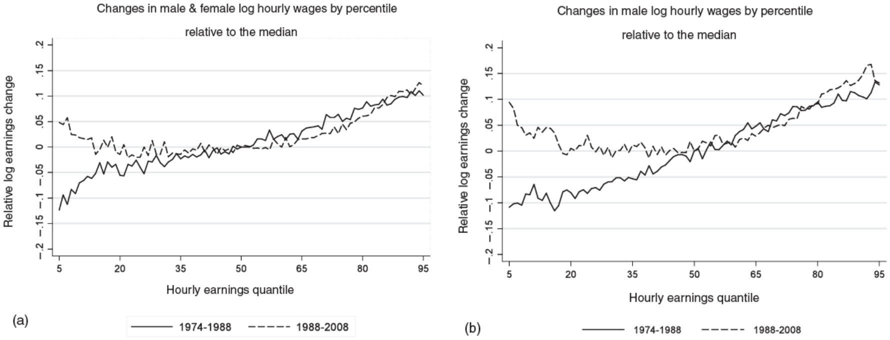
# Extensions (1): Acemoglu and Autor (2011)




Source: Acemoglu and Autor (2011)

- Katz and Murphy (1992) model fits post-1995 data poorly
- SBTC in recent periods may affect middle- (as opposed to low-) skilled workers: wage/job “polarization”

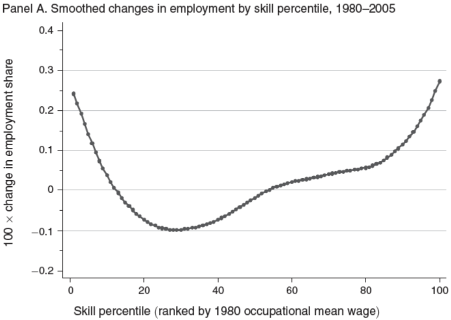
# “Wage Polarization”




Source: Acemoglu and Autor (2011)

- Larger (male, female) high/low-end wage growth wrt. median (but low-end growth could be affected by min. wage increases?)
- Contrasts w/ monotonic rise in education wage premium and “canonical” model

# “Job Polarization”




Source: Autor and Dorn (2013)

- Larger employment growth in high/low-skill occupations wrt. median-skill ones (challenged!)
- Criticisms: i) lower-tail findings not replicable w/ CPS data (Mishel et al., 2013); ii) lower-tail job loss non-gradual/mostly recession-driven (Beaudry et al., 2016)

# Extensions (2): Deming and Kahn (2018) Data

- Variation in skill demand vs. wages/firm performance? ▸ relevant literature
- Online job posting microdata from "Burning Glass Technologies" (BG) ▸ skill requirements for Metropolitan Statistical Areas (MSAs), MSA wages from OES survey, firm data from Compustat
- Focus on:
  - "Cognitive" ("problem solving","research", "analytical": matches "non-routine analytical" (Autor et al., 2003))
  - "Social" ("communication", "teamwork", "collaboration": matches (Deming, 2017))

# Extensions (2): Deming and Kahn (2018) Specifications

$$\log(\text{Wage})_{om} = \alpha + \overline{\text{Skill}}_{om}\beta' + \text{Controls} + \epsilon_{om}$$

- ***Wage$_{om}$*** and ***Skill$_{om}$*** median MSA($m$)-occupation($o$) hourly wage and (average) skill requirement

$$Firm\_perf_f = \alpha_0 + \overline{Skill}_f\beta' + \bar{I}^o_f + \bar{X}_f\gamma' + \bar{I}^m_f + \theta_n + \epsilon_f$$

- ***Skill$_f$*** average shares of ads per requirement, ***$I^o$*** share of postings per occupation, ***$I^m$*** ad-weighted average MSA characteristics: all firm $f$-level
- ***Firm_perf$_f$***: indicator for public listing: publicly traded $f$ generally larger, higher-paying, more successful (is this correlated with demand for given skills?)
- ***Firm_perf$_f$*** also: revenue/worker (in publicly traded firm $f$): proxy for productivity (are firm skill demand differences associated w/ differences in bottom line?)
- Controls: "Base": MSA characteristics, 4-digit SOC occupation FE; "Detailed": MSA/6-digit SOC occupation FEs, industry shares

# Main Results (1): Skill Demand & Wages

$$\log(\text{Wage})_{om} = \alpha + \overline{\text{Skill}}_{om}\beta' + \text{Controls} + \epsilon_{om}$$

**Table 3**
**Average Wages and Skill Requirements**

| | Dependent Variable: Log(Mean Wages) in MSA-Occupation Cells | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Cognitive | .113*** | −.413*** | .245*** | .181*** | .0792*** | .0465*** |
| | (.00908) | (.0166) | (.00784) | (.0139) | (.00873) | (.0122) |
| Social | .429*** | −.0919*** | .301*** | .236*** | .0517*** | .0202 |
| | (.0155) | (.0206) | (.0121) | (.0167) | (.00966) | (.0127) |
| Both required | | 1.319*** | | .157*** | | .0760*** |
| | | (.0349) | | (.0278) | | (.0198) |
| Years of education | .131*** | .129*** | .0764*** | .0765*** | .00865*** | .00873*** |
| | (.000770) | (.000763) | (.000844) | (.000844) | (.000995) | (.000995) |
| Years of experience | .160*** | .161*** | .0848*** | .0849*** | .0318*** | .0318*** |
| | (.00120) | (.00118) | (.00120) | (.00120) | (.00102) | (.00102) |
| Base controls | | | X | X | | |
| Detailed controls | | | | | X | X |
| *F*-statistic (cognitive and social) | 553.1 | 855.0 | 1,004 | 680.4 | 69.66 | 51.35 |
| *F*-statistic (all 10 skills) | 1,874 | 2,054 | 612.6 | 560.1 | 59.93 | 55.83 |
| MSA-occupation cells | 56,611 | 56,611 | 56,611 | 56,611 | 56,611 | 56,611 |
| $R^2$ | .702 | .710 | .846 | .846 | .940 | .941 |

Source: Deming and Kahn (2018)

# Skill Demand & Wages: Interpretation

- 10 ppt increase in share of vacancies requiring cognitive skills associated w/ 1.1% higher wages (Col. 1)
- 1 s.d. increase (0.10) in share of vacancies requiring both cognitive and social skills associated w/ 14% higher wages (Col. 2)
- Results robust to highly controlled specifications (Cols. 5, 6)
- Take-aways: i) positive, significant relationship between high-skill requirements and wages; ii) social-cognitive skill complementarity (e.g., positive return for cognitive skills nearly triples when social skills also required)

# Main Results (2): Skill Demand & Firm Performance

$$Firm\_perf_f = \alpha_0 + \overline{Skill}_f \beta' + \bar{I}_f^o + \bar{X}_f \gamma' + \bar{I}_f^m + \theta_n + \epsilon_f$$

**Table 4**
**Firm Outcomes and Average Skill Requirements**

| | Publicly Traded | | | | Log(Revenue per Worker) | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Cognitive | .0131 | −.170*** | .0318** | −.136*** | .469*** | .624*** | .379*** | .0761 |
| | (.0122) | (.0180) | (.0129) | (.0185) | (.117) | (.190) | (.136) | (.218) |
| Social | .162*** | .0165 | .0934*** | −.0364** | .218** | .348** | .239* | −.00813 |
| | (.0114) | (.0115) | (.0115) | (.0154) | (.105) | (.164) | (.123) | (.185) |
| Both required | | .365*** | | .328*** | | −.268 | | .531* |
| | | (.0262) | | (.0260) | | (.259) | | (.298) |
| Years of education | −.00212 | −.00141 | −.00242* | −.00203 | .00423 | .00312 | .00979 | .00974 |
| | (.00134) | (.00134) | (.00135) | (.00135) | (.0222) | (.0222) | (.0266) | (.0266) |
| Years of experience | .0236*** | .0239*** | .0125*** | .0128*** | .0851*** | .0839*** | .119*** | .120*** |
| | (.00150) | (.00150) | (.00157) | (.00157) | (.0144) | (.0145) | (.0182) | (.0182) |
| Base controls | X | X | | | X | X | | |
| Detailed controls | | | X | X | | | X | X |
| *F*-statistic (cognitive and social) | 110.2 | 138.1 | 41.93 | 81.19 | 12.43 | 8.644 | 6.560 | 5.432 |
| *F*-statistic (all 10 skills) | 181.6 | 183.1 | 130.3 | 133.2 | 10.96 | 10.06 | 4.072 | 3.993 |
| Number of firms | 85,695 | 85,695 | 85,695 | 85,695 | 3,622 | 3,622 | 3,622 | 3,622 |
| $R^2$ | .246 | .248 | .330 | .332 | .511 | .511 | .736 | .737 |

Note.—Observations are at the firm level, weighted by number of ads posted by the firm. All regressions control for the share of ads with each of the eight other job skill, education, and experience requirements. Years of education and experience equal 0 if the firm has no ads that specify requirements. In col. 1–4, the dependent variable is an indicator equal to 1 if the firm can be matched to Compustat; in col. 5–8, it is equal to the log of revenue per worker, conditional on being matched to Compustat. Base controls include two-digit North American Industry Classification System industry fixed effects and the ad-weighted distributions of four-digit occupation fixed effects and metropolitan statistical area (MSA) characteristics from the American Community Survey. Detailed controls include industry fixed effects and the ad-weighted distributions of MSA and six-digit Standard Occupational Classification occupation fixed effects. See table 1 for skills definitions.

Source: Deming and Kahn (2018)

# Skill Demand & Firm Performance: Interpretation

- Cols. 1–4: effect on probability of being publicly traded (e.g., 1 s.d. increase in share vacancies requiring social skills associated w/ 3.2 ppt. increase in the public trading probability in Col. 1)
- Cols. 5–8: effect on productivity proxy or log(revenue)/worker (sample: 30% of ads; gains in ads w/ joint requirement, e.g. Col. 8)
- Take-aways: i) positive relationship between high-skill requirements and firm performance across specifications; ii) further evidence of social-cognitive skill complementarity

# Premise (1): Definitions

- **Skill**: worker's stock of capability to perform given task(s) (e.g., Heckman and Sedlacek (1985))
- **Task**: unit of work activity producing output (Acemoglu and Autor, 2011) via skill utilization
- Tasks vary by degree of **routineness** (Deming, 2017) ▸ Examples:
  - **Routine**: well-established/correct way to perform it (Deming, 2017); can be automated via explicit, programmed rules (Autor et al., 2003).
  - **Non-routine**: rules cannot be specified mechanically
  - Both can be divided into:
    - **Cognitive/Analytic**: demanding regarding flexibility, creativity, generalized problem-solving, and complex communications (Autor et al., 2003)
    - **Manual**: physically demanding (Autor and Handel, 2013)

# Premise (2): The "Task Approach"

- Tasks as proxy for "jobs" or services provided; task is occupation (which may require multiple skills as inputs, depending on technology); "canonical" model does not distinguish b/w tasks and skills (i.e., imposes 1:1 mapping b/w the two)
- Workers highly productive in given tasks self-select into occupations paying differential wages (Autor and Handel, 2013)
- Mapping from skill content to tasks/wages highly affected by SBTC (Acemoglu and Autor, 2011); skills may be repurposed away from obsolete tasks
- Does task = f(skills), e.g., task specialization based on skill profile (Deming, 2017)? If so, could represent results wrt. skills
- What is f and how does f(skill content of the task) change over time?
- All of the above hinges on definition of skills, tasks and their classifications into different types (unclear in literature - e.g., Acemoglu and Autor (2011) definition of tasks very precise but not universally applied)

# Premise (3): Task Measurement

- Occupational Information Network (O*NET) data since 1998 (successor of Dictionary of Occupational Titles, DOT)
  - Matches 12,000 DOT job codes to 1,102 O*NET "occupational units"; data self-reported by workers
  - 277 occupational descriptors
  - Example: Caines et al. (2017a) used 2015 O*NET to classify occupations by complexity
- Example of other measures: labor force data (e.g., IBB/IAB in Germany)
- Consistency in task coding over time needed to ensure sound analyses of trends in task allocation, etc.

# Premise (4): Trends in Measured Tasks

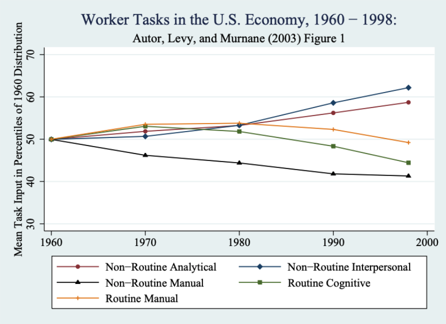



Figure 1. Autor, Levy and Murnane (2003) Figure I

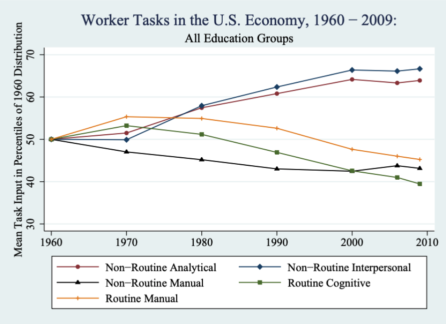



Figure 2. Replication and Extension of ALM Figure 1: 1960 - 2009

Source: Autor and Price (2013)

- Changes in task input wrt. 1960 distribution, measured in percentiles
- Steady rise in non-routine analytical/interpersonal task (∼more "complex") input over time
- Routine-cognitive (e.g., bookkeeping and data entry) vs. routine-manual (e.g., repetitive assembly-line production) tasks

# Skills and Tasks: Hershbein and Kahn (2018)

- Does (educational, experiential, cognitive, computer) skill demand vary by MSA following Great Recession? Also use BG data:

$$outcome_{gmt} - outcome_{gm2007} = \alpha_0 + \left[ shock_m \times I^t \right] \alpha_1 + I^t + X^t + \varepsilon_{gmt}$$

- $\boldsymbol{outcome_{gmt} - outcome_{gm2007}}$: change in skill demand for MSA $m$ in year $t$ (2010-2015), and occupation/firm group $g$ wrt. $t = 2007$
- $\boldsymbol{shock_m}$: MSA-specific employment shock as $\Delta$(projected employment growth) from peak (2006) to recession (2009); scaled s.t. 1-unit change is difference b/w 10th and 90th percentile MSAs (large values as worse shocks):

$$\Delta \hat{E}_{mt} = \sum_{k=1}^{K} \phi_{m,k,\tau} (\ln E_{kt} - \ln E_{k,t-1}), \;\; shock_m = \Delta \hat{E}_{m2009} - \Delta \hat{E}_{m2006}$$

- $\boldsymbol{\phi_{m,k,\tau}}$: industry $k$ employment share in MSA $m$, year $\tau$ (2004-2005 avg.); $\boldsymbol{E_{k,\tau}}$: national employment in industry $k$, year $t$
- Shock calculation takes care of measurement error in MSA employment growth and captures impact of local labor demand

# Main Results (1): MSA-level "Upskilling" Demand

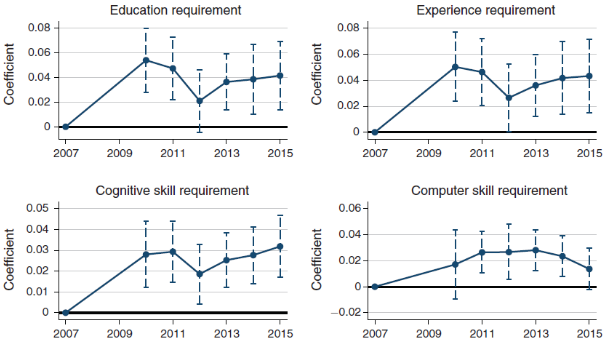



FIGURE 2. SKILL REQUIREMENTS AND THE MSA-SPECIFIC EMPLOYMENT SHOCK

Source: Hershbein and Kahn (2018)

- $\boldsymbol{\alpha_1}$: effect across MSAs from $shock_m$-and-year dummy $I^t$ interaction on $\Delta$(share ads posting any skill requirement)
- "Dip" in 2012 due to lack of BG data availability
- "Upskilling" starkest in most-impacted MSAs

# Main Results (2): Within-occupation "Upskilling" Demand

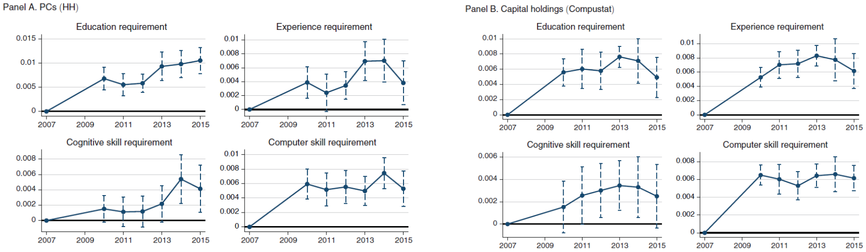
Table 2—Within-Occupation Changes in Skill Requirements

| | Education (1) | Experience (2) | Cognitive (3) | Computer (4) |
|---|---|---|---|---|
| Shock × 2010 | 0.0526 | 0.0490 | 0.0275 | 0.0203 |
| | (0.0135) | (0.0134) | (0.00726) | (0.00859) |
| Shock × 2011 | 0.0475 | 0.0443 | 0.0281 | 0.0243 |
| | (0.0131) | (0.0134) | (0.00731) | (0.00716) |
| Shock × 2012 | 0.0233 | 0.0253 | 0.0186 | 0.0207 |
| | (0.0128) | (0.0136) | (0.00693) | (0.00848) |
| Shock × 2013 | 0.0400 | 0.0363 | 0.0253 | 0.0252 |
| | (0.0120) | (0.0122) | (0.00642) | (0.00664) |
| Shock × 2014 | 0.0429 | 0.0436 | 0.0265 | 0.0227 |
| | (0.0143) | (0.0140) | (0.00657) | (0.00679) |
| Shock × 2015 | 0.0488 | 0.0468 | 0.0300 | 0.0134 |
| | (0.0143) | (0.0142) | (0.00730) | (0.00807) |
| Number Occ-MSA-Year Cells | 193,086 | 193,086 | 178,176 | 178,176 |
| $R^2$ | 0.044 | 0.069 | 0.040 | 0.034 |

Source: Hershbein and Kahn (2018)

- Main specification again, but at occupation-MSA-year level
- Magnitude/persistence comparable to MSA-level effects
- Results not driven by changes in the occupation mix of postings, but by increased skill requirements within similar types of jobs

# Main Results (3): “Upskilling” and Capital Investment




Source: Hershbein and Kahn (2018)

- Add: $[shock_m \times I^t \times Capital_f]\alpha_2$; $Capital_f$ change in PC/PPE investment as $\Delta$ b/w 2010/2012/2014 & 2002/2004/2006 avgs.
- $\boldsymbol{\alpha_2}$: in harder-hit MSAs, high-investment firms increase likelihood of posting requirements wrt. low-investment ones
- Requirements all complement routine-biased technologies, so “upskilling” reflects changes in production inputs; physical + human capital deepening within same firms

# Main Results (4): "Upskilling" and Job Types

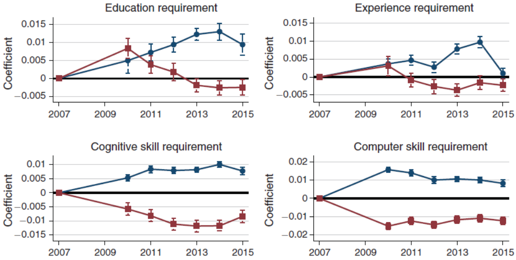



Figure 6. Differential Upskilling for Routine Occupations

Source: Hershbein and Kahn (2018)

- Add: $[shock_m \times I^t \times Routine^i_o]\alpha_2$; $Routine^i_o = 1$ if job $o$ in top-quartile wrt. routine-cognitive/-manual classification by Acemoglu and Autor (2011)
- $\boldsymbol{\alpha_2}$: additional effect for top-quartile jobs wrt. effect in bottom 3 quartiles of each type (blue: cognitive; red: manual)
- Greater degree of "upskilling" in routine-cognitive jobs

# Main Results (5): Job Types and Labor Market Outcomes

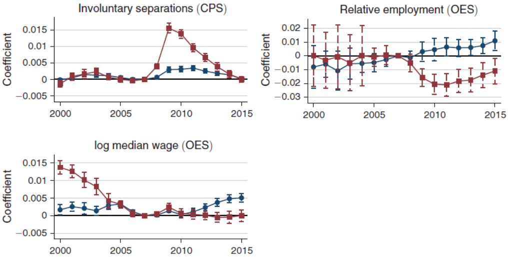



FIGURE 7. DIFFERENTIAL EMPLOYMENT AND WAGE EFFECTS FOR ROUTINE OCCUPATIONS

Source: Hershbein and Kahn (2018)

- Changes in wages/employment/separations as additional outcomes
- Idea: routine-cognitive labor complementary via "upskilling"; routine-manual labor substituteable
- Evidence: drop/no change (rise) in routine-manual (-cognitive) employment/wages; higher involuntary layoffs for routine-manual jobs

# Main Idea: Task-Biased Technological Change (TBTC)

### Case 1: Routine TBTC (RTBTC)

- Example: Autor and Dorn (2013)

### Case 2: Complex TBTC (CTBTC)

- Example: Caines, Hoffmann and Kambourov (2017a)
- Example: Caines, Hoffmann, Kambourov et al. (2017b)

# Routine TBTC: Autor and Dorn (2013)

- Punchline: wage/job "polarization" due to RTBTC as a result of automation; model: workers as suppliers of: i) routine (R) or ii) abstract (A) or iii) manual (M) tasks
- 722 Commuting Zones/CZs (groups of counties with strong commuting ties) capture local labor markets (cover entire US, economically meaningful, available for entire period)
- Occupation $k$-specific routine task intensity:

$$RTI_k = \ln(T^R_{k,1980}) - \ln(T^M_{k,1980}) - \ln(T^A_{k,1980})$$

- Routine employment share ($RSH_{jt}$) by commuting zone $j$ in time $t$ using occupation-zone-time-specific employment $L_{jkt}$:

$$RSH_{jt} = \left( \sum_{k=1}^{K} L_{jkt} \cdot \mathbb{1}\left[ RTI_k > RTI^{P66} \right] \right) \left( \sum_{k=1}^{K} L_{jkt} \right)^{-1}$$

- $\mathbb{1}$ indicator if $k$ is "routine" (i.e., in 1980 top employment-weighted third of $RTI_k$ distribution)

# Routine Intensity and Automation (1)

$$\Delta PC_{jst} = \delta_t + \beta_0 \times RSH_{jst_0} + \gamma_s + e_{jst}$$

TABLE 3—COMPUTER ADOPTION AND TASK SPECIALIZATION WITHIN COMMUTING ZONES, 1980–2005
(*Dependent variables: 10 × annual change in adjusted PCs per employee, 10 × annual change in employment share of routine occupations*)

| | (1) | (2) | (3) |
|---|---|---|---|
| *Panel A. Δ Adjusted PCs per employee, 1980–2000* | | | |
| | 1980–1990 | 1990–2000 | 1980–2000 |
| Share of routine occs$_{-1}$ | 0.695*** | 0.490*** | 0.619*** |
| | (0.061) | (0.076) | (0.044) |
| $R^2$ | 0.577 | 0.332 | 0.385 |
| *Panel B. Δ Share routine occupations, 1980–2005* | | | |
| | All workers | College | Noncollege |
| Share of routine occs$_{-1}$ | −0.254*** | −0.153*** | −0.295*** |
| | (0.023) | (0.024) | (0.018) |
| $R^2$ | 0.433 | 0.206 | 0.429 |

Source: Autor and Dorn (2013)

- $\boldsymbol{\Delta PC_{jst}}$ "adjusted PCs/employee firm" purged of industry-establishment size FEs (though imperfect measure of tech adoption); year ($\boldsymbol{\delta_t}$) and state ($\boldsymbol{\gamma_s}$) FEs
- $\beta$ identified by within-State, cross-CZ variation

# Routine Intensity and Automation (2)

TABLE 3—COMPUTER ADOPTION AND TASK SPECIALIZATION WITHIN COMMUTING ZONES, 1980–2005
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| | (0.023) | (0.024) | (0.018) |
| $R^2$ | 0.433 | 0.206 | 0.429 |

Source: Autor and Dorn (2013)

- Routine intensity associated w/ computerization
- Routine-intense zones associated w/ fall in routine-intense occupations

# Positive relationship b/w lagged routine employment share and growth in service employment

TABLE 5—ROUTINE EMPLOYMENT SHARE AND GROWTH OF SERVICE EMPLOYMENT WITHIN COMMUTING ZONES, 1980–2005: STACKED FIRST DIFFERENCES, OLS AND 2SLS ESTIMATES
(*Dependent variable: 10 × annual change in share of noncollege employment in service occupations*)

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| *Panel A. OLS estimates: covariates specified in lagged levels* | | | | | | | |
| Share of routine occs$_{-1}$ | 0.105*** | 0.066* | 0.066** | 0.110*** | 0.110** | 0.069* | 0.111*** |
| | (0.032) | (0.036) | (0.029) | (0.031) | (0.049) | (0.035) | (0.034) |
| College/noncollege pop$_{-1}$ | | 0.012*** | | | | | 0.011** |
| | | (0.004) | | | | | (0.005) |
| Immigr/noncollege pop$_{-1}$ | | | 0.042** | | | | 0.025** |
| | | | (0.017) | | | | (0.011) |
| Manufact/empl$_{-1}$ | | | | −0.056*** | | | −0.036*** |
| | | | | (0.015) | | | (0.011) |
| Unemployment rate$_{-1}$ | | | | −0.067 | | | −0.313*** |
| | | | | (0.069) | | | (0.068) |
| Female empl/pop$_{-1}$ | | | | | −0.044 | | −0.200*** |
| | | | | | (0.039) | | (0.037) |
| Age 65+/pop$_{-1}$ | | | | | −0.114*** | | −0.061*** |
| | | | | | (0.035) | | (0.020) |
| Share workers with wage$_t$ < min wage$_{t+1}$ | | | | | | −0.134*** | −0.197*** |
| | | | | | | (0.020) | (0.029) |
| $R^2$ | 0.179 | 0.189 | 0.196 | 0.195 | 0.191 | 0.196 | 0.233 |
| *Panel B. 2SLS estimates: covariates specified in lagged levels* | | | | | | | |
| Share of routine occs$_{-1}$ | 0.192*** | 0.118*** | 0.148*** | 0.162*** | 0.218*** | 0.174*** | 0.149*** |
| | (0.035) | (0.046) | (0.044) | (0.031) | (0.054) | (0.035) | (0.056) |
| $R^2$ | 0.169 | 0.186 | 0.189 | 0.192 | 0.182 | 0.182 | 0.264 |
| *Panel C. 2SLS estimates: covariates specified in ten year changes* | | | | | | | |
| Share of routine occs$_{-1}$ | 0.192*** | 0.173*** | 0.152*** | 0.170*** | 0.180*** | 0.174*** | 0.112** |
| | (0.035) | (0.043) | (0.032) | (0.035) | (0.035) | (0.035) | (0.044) |
| $R^2$ | [illegible] | [illegible] | [illegible] | [illegible] | [illegible] | [illegible] | [illegible] |

# Interpretation

- Intuition: polarization in US employment explained (in part) by rising employment in low-skill service occupations
- Panel A: $\Delta SVC_{jst} = \delta_t + \beta_1 RSH_{jt_0} + \mathbf{X}'_{jt_0}\beta_2 + \gamma_s + e_{jst}$
- Panels B,C: 2SLS w/ instrument:

$$\widetilde{RSH}_j = \sum_{i=1}^{I} E_{i,j,1950} \times R_{i,-j,1950}$$

- Interact 1950 employment in industry $i$, CZ $j$ w/ US-wide (excl. CZ $j$) routine occupation share in industry $i$: predicted value for routine employment share in each CZ; depends only on 1950 national occupation and local industry mix (so correlated w/ long-term component of routine shares only)
- 2SLS idea: isolate stable differences in production structure across CZs as source of variation (OLS biased due to potential cyclical fluctuations, e.g. local labor demand shocks)
- Typically 2SLS > OLS (e.g., .15 vs. .1 under Col. 7)

# Wages/employment shares in high-routine content occupations

Table 7—Routine Employment Share and Change in Occupational Employment Shares and Wage Levels within Commuting Zones, 1980–2005: 2SLS and Reduced Form OLS Estimates
(*Dependent variable: 10 × annual change in share of noncollege employment by occupation; log real hourly wage*)

| | | I. Occupations with low routine content | | | II. Occupations with high routine content | | |
|---|---|---|---|---|---|---|---|
| | | Service occs | Transport, construct, mechanics, mining, farm | Managers, prof, tech, finance, public safety | Administrative support, retail sales | Precision production, craft workers | Machine operators, assemblers |
| | | (1) | (2) | (3) | (4) | (5) | (6) |
| *Panel A. Change in share of noncollege employment* | | | | | | | |
| (i) All | Share of routine $\text{occs}_{-1}$ | 0.192*** | 0.248*** | 0.028 | −0.277*** | −0.085*** | −0.107** |
| | | (0.035) | (0.037) | (0.029) | (0.038) | (0.017) | (0.044) |
| (ii) Males | Share of routine $\text{occs}_{-1}$ | 0.210*** | 0.246*** | −0.043 | −0.055* | −0.145*** | −0.213*** |
| | | (0.027) | (0.046) | (0.036) | (0.030) | (0.026) | (0.046) |
| (iii) Females | Share of routine $\text{occs}_{-1}$ | 0.253*** | 0.002 | 0.117*** | −0.431*** | −0.028** | 0.087 |
| | | (0.073) | (0.045) | (0.030) | (0.062) | (0.012) | (0.055) |
| *Panel B. log hourly wages of noncollege workers* | | | | | | | |
| (i) All | Share of routine $\text{occs}_{80} \times 2005$ | 0.381*** | 0.023 | 0.433*** | 0.337*** | −0.078 | −0.388*** |
| | | (0.091) | (0.099) | (0.113) | (0.082) | (0.109) | (0.085) |
| (ii) Males | Share of routine $\text{occs}_{80} \times 2005$ | 0.346*** | 0.015 | 0.287* | 0.187* | −0.075 | −0.374*** |
| | | (0.132) | (0.097) | (0.149) | (0.097) | (0.140) | (0.106) |
| (iii) Females | Share of routine $\text{occs}_{80} \times 2005$ | 0.328*** | 0.310* | 0.618*** | 0.468*** | −0.223 | −0.415*** |
| | | (0.095) | (0.183) | (0.116) | (0.092) | (0.139) | (0.105) |

Source: Autor and Dorn (2013)

# Interpretation

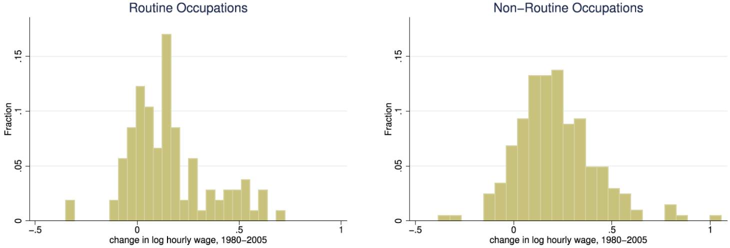
- Panel B Specification:

$$\ln w_{ijkt} = \gamma_{jk} + \lambda_k \left\{ RSH_{j,1980} \times \mathbb{1}[t = 2005] \right\} + \mathbf{X}_i' \beta_t + \delta_{kt} + \phi_{st} + e_{ijkt}$$

- $RSH_{j,1980}$ (instrumented) start-of-period routine employment share
- $\lambda_k \left\{ RSH_{j,1980} \times \mathbb{1}[t = 2005] \right\}$ measures impact of CZ 1980 routine-intensity on 1980–2005 wage growth
- Higher (non-College) services sector worker wages in high-routine share CZs (7 ppt higher routine share in 1980 predicts 3 log points greater wage growth in service occupations between 1980 and 2005); opposite in manual ("assembler") occupations
- Bottom line: rise in low-skill services explains relatively large wage growth among occupations with relatively low wages in 1980

# CTBTC: Premise

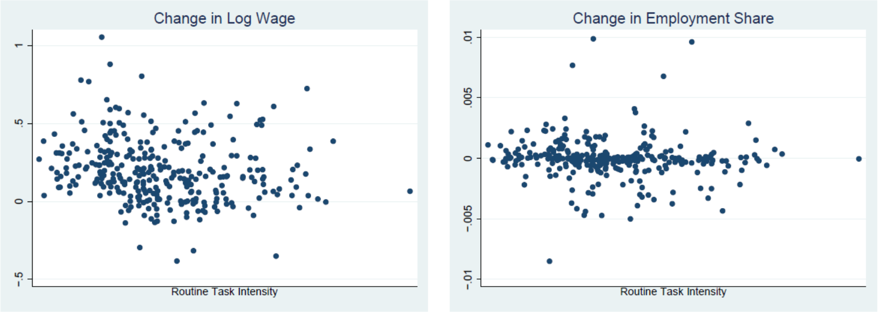
- BUT (!): 1980 Census Integrated Public Use Microdata (Census) and 2005 American Community Survey (ACS) show both routine, non-routine occupations undergo low- and high-wage growth
- Craft (i.e., routine-manual) occupations saw wage growth in past decades - contrary to RTBTC predictions (Katz, 2014)
- Goal: go beyond explaining mean outcomes by wage level; instead explain occupation-level variance in outcomes




Source: Caines et al. (2017a)

# Side Note: Routineness and Occupations (1)

Figure 3: Wage and Employment Growth by Routine Task Intensity




Notes: Data taken from the 1980 5% Sample of the US Census and the 2005 American Community Survey (ACS). Hourly wages constructed from total wage and salary data (adjusted using PCE deflator), number of weeks worked per year, and usual number of hours worked per year. Data is defined on the 3-digit occupation level.

Source: Caines et al. (2017b)

- Occupation-level differences in Autor and Dorn (2013) “routineness” do not explain 1980-2005 wage/employment growth variation

# Measuring "Complexity"

- "Complexity index" of occupations using O*NET data:
  - 35 occupational descriptors selected/aggregated using PCA into single measure of "task complexity":

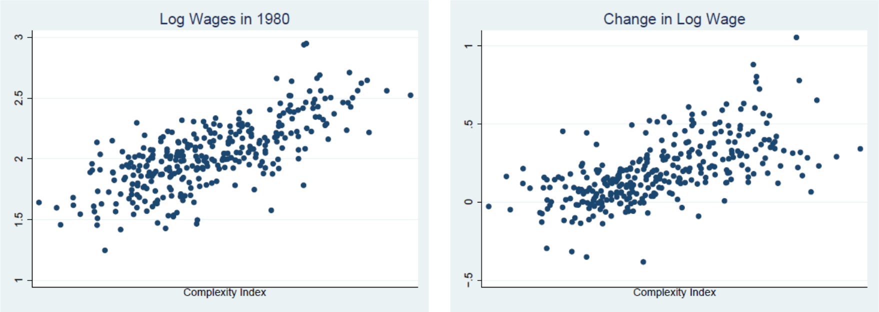
$$C_o = \gamma \cdot X_o$$

$$\gamma = \underset{\arg\min}{\gamma} \sum_o \|X_o - C_o \cdot \gamma'\|$$

    where: $C_o$ complexity score for occupation $o$, $\gamma$ factor loading vector and $X_o$ O*NET descriptor vector
  - Occupations ranked above 66th percentile of the complexity index are regarded complex, and vice versa
  - Top 10%: professional/scientific/medical, senior mgmt, etc.
  - Bottom 10%: service and manual, etc.
- Routine task-intensity index as in Autor and Dorn (2013) Detail

# Side Note: Complexity and Occupations (2)

Figure 4: Wage Levels and Wage Growth by Complexity




Notes: Data taken from the 1980 5% Sample of the US Census and the 2005 American Community Survey (ACS). Hourly wages constructed from total wage and salary data (adjusted using PCE deflator), number of weeks worked per year, and usual number of hours worked per year. Data is defined on the 3-digit occupation level.

Source: Caines et al. (2017b)

- Complexity associated w/ increases in 1980 wage levels/1980-2005 wage growth at occupation level (weaker association w/ employment)

# CTBTC: Caines, Hoffmann and Kambourov (2017a)

- How is task complexity related to wages and employment (both level and growth)? Is task routineness still significant after taking complexity into account?
- "Complex" Task: higher-order, relatively scarce abilities - abstract/solve problems, make decisions, communicate effectively
- "Simple" Occupation: raw physical, cognitive, and interactive skills only; abundant labor supply
- Examples:

| | Simple | Complex |
|---|---|---|
| Routine | Bank tellers | Statistical clerks |
| Non-routine | Waiters and waitresses | Physicians |

Source: Autor et al. (2003); Caines et al. (2017a)

Table3

# Task Complexity and Individual Wage Level

**Table 4**
Individual-level wage regression, 1980 and 2005.

| Dependent variable: log wages | | |
|---|---|---|
| Independent variable | 1980 | 2005 |
| Complexity index | 0.347*** | 0.711*** |
| | (7.25) | (14.32) |
| Routine index | −0.0154 | 0.0157 |
| | (−0.34) | (0.31) |
| *N* | 2664259 | 673783 |

Notes: The regressions include fixed effects for age (4 categories: 16–28, 29–40, 41–52, 53–64), education level (less than high school, high school, some college, college), and race (white, nonwhite). Standard errors clustered at occupation level. t-statistics are in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Source: Caines et al. (2017a)

- 1980 Census and 2005 ACS; consists of non-farm workers in mainland US, aged 14-16, mainly males
- Task complexity positively associated w/ wages at individual (and occupational) levels
- Controlling for complexity, no significant relationship b/w routineness and mean wage

# Complexity & Occupational Wage Level: Results

**Table 5**
Occupation-level wage regression with occupational demographic controls.

| Independent variable | (A) Dependent variable: log wages in 1980 | | | | (B) Dependent variable: log wages in 2005 | | | |
|---|---|---|---|---|---|---|---|---|
| | Complex variable: index | | Complex variable: indicator[a] | | Complex variable: index | | Complex variable: indicator[a] | |
| | (i) | (ii) | (iii) | (iv) | (v) | (vi) | (vii) | (viii) |
| Complexity variable | 0.102* | 0.106* | 0.00228 | 0.0235 | 0.401*** | 0.416*** | 0.115*** | 0.0862** |
| | (1.71) | (1.75) | (0.08) | (0.79) | (5.31) | (5.45) | (3.29) | (2.19) |
| Routine index | | 0.0131 | 0.00442 | 0.00846 | | 0.0512 | 0.0394 | 0.0317 |
| | | (0.41) | (0.14) | (0.26) | | (1.28) | (0.95) | (0.76) |
| Female share | −0.143*** | −0.147*** | −0.154*** | −0.155*** | −0.128** | −0.143*** | −0.159*** | −0.174*** |
| | (−3.52) | (−3.51) | (−3.68) | (−3.71) | (−2.53) | (−2.76) | (−2.97) | (−3.24) |
| College share | 0.260*** | 0.265*** | 0.325*** | 0.295*** | 0.530*** | 0.553*** | 0.715*** | 0.676*** |
| | (3.49) | (3.50) | (4.64) | (3.74) | (5.71) | (5.85) | (8.01) | (6.61) |
| High school share | 0.427*** | 0.423*** | 0.468*** | 0.478*** | 0.361** | 0.345** | 0.441*** | 0.568*** |
| | (3.50) | (3.45) | (3.84) | (3.97) | (2.35) | (2.24) | (2.80) | (3.64) |
| Non-white share | −0.284 | −0.282 | −0.269 | −0.279 | −0.172 | −0.164 | −0.0910 | −0.139 |
| | (−1.38) | (−1.37) | (−1.30) | (−1.35) | (−0.67) | (−0.64) | (−0.35) | (−0.52) |
| Married share | 0.884*** | 0.868*** | 0.938*** | 0.922*** | 0.568* | 0.509 | 0.701** | 0.717** |
| | (3.47) | (3.37) | (3.66) | (3.60) | (1.79) | (1.59) | (2.14) | (2.17) |
| Mean age | 0.00845** | 0.00851** | 0.00835** | 0.00844** | 0.0104** | 0.0106** | 0.00822 | 0.00991* |
| | (2.16) | (2.17) | (2.11) | (2.14) | (2.09) | (2.13) | (1.61) | (1.92) |
| Mean # children | −0.0710 | −0.0644 | −0.0661 | −0.0699 | 0.0437 | 0.0692 | 0.0789 | 0.0583 |
| | (−0.64) | (−0.57) | (−0.59) | (−0.62) | (0.31) | (0.49) | (0.54) | (0.39) |
| *N* | 315 | 315 | 315 | 315 | 310 | 310 | 310 | 310 |

Source: Caines et al. (2017a)

# Complexity & Occupational Wage Level: Interpretation

- Regressions of log of mean occupational wages on task complexity and routine task intensity, controlling for an array of demographics
- Percentile of complexity index used, w/ interpretation that:
    - mean wages of individuals in most complex occupations are 10% higher than those in least complex occupations (Cols. (i) and (ii))
    - gap b/w mean wage in the most and least complex occupations at 40% in 2005 (Cols. (v) and (vi))
- Controlling for complexity, no significant relationship b/w routineness and mean wage at occupation level

# Complexity & Occupational Wage Growth: Results

**Table 6**
Occupation-level wage growth regression with occupational demographic means.

| Dependent variable: change in log wages 1980–2005 | | | | | |
|---|---|---|---|---|---|
| Independent variable | Complex variable: index | | | Complex variable: indicator[a] | |
| | (i) | (ii) | (iii) | (iv) | (v) |
| Complexity variable | 0.304*** | 0.316*** | 0.347*** | 0.138*** | 0.0683** |
| | (4.94) | (5.07) | (5.74) | (5.02) | (2.18) |
| Routine index | | 0.0398 | 0.0336 | 0.0262 | 0.0161 |
| | | (1.21) | (1.05) | (0.81) | (0.48) |
| Female share | 0.00599 | −0.00561 | −0.0299 | −0.0267 | −0.0504 |
| | (0.15) | (−0.13) | (−0.71) | (−0.63) | (−1.15) |
| College share | 0.270*** | 0.288*** | 0.287*** | 0.349*** | 0.381*** |
| | (3.56) | (3.73) | (3.52) | (4.37) | (4.35) |
| High school share | −0.102 | −0.115 | 0.0629 | 0.119 | 0.235* |
| | (−0.82) | (−0.91) | (0.50) | (0.94) | (1.81) |
| Non-white share | 0.106 | 0.112 | 0.0181 | 0.100 | 0.0551 |
| | (0.51) | (0.54) | (0.09) | (0.49) | (0.26) |
| Married share | −0.244 | −0.290 | 0.0537 | 0.232 | 0.209 |
| | (−0.94) | (−1.11) | (0.20) | (0.87) | (0.76) |
| Mean age | 0.00207 | 0.00222 | 0.00364 | 0.000595 | 0.00271 |
| | (0.51) | (0.55) | (0.90) | (0.15) | (0.64) |
| Mean # children | 0.0549 | 0.0747 | 0.00478 | −0.0198 | −0.00485 |
| | (0.48) | (0.64) | (0.04) | (−0.17) | (−0.04) |
| Order of 1980 wage poly. | 0 | 0 | 3 | 3 | 3 |
| $N = 310$ | | | | | |

Notes: Demographic variables are occupation-level means of the share of workers in an occupation with a college/high-school degree, the share of workers in an occupation who are non-white, the share of workers in an occupation who are married, the share of female workers in an occupation, the mean age of workers in an occupation, and the mean number of children of workers in an occupation. t-statistics are in parentheses. Significance levels are: *** 1%, ** 5%, * 10%.

[a] Complex occupations are defined as those above the 50th percentile (column (iv)) or above the 66th percentile (column (v)) of the complexity index.

Source: Caines et al. (2017a)

- Same for wage growth at occupational (3-digit DOT/O*NET) and group levels Tables 8,9

# Task Complexity and Occupational Employment

**Table 7**
Occupation-level employment growth regression with occupational demographic means.

| Dependent variable: change in employment share 1980–2005 | | | | | |
|---|---|---|---|---|---|
| Independent variable | Complex variable: index | | | Complex variable: indicator[a] | |
| | (i) | (ii) | (iii) | (iv) | (v) |
| Complexity variable | 0.00162 | 0.00135 | 0.00154 | 0.00000113 | 0.000876 |
| | (1.44) | (1.19) | (1.34) | (0.00) | (1.56) |
| Routine index | | −0.000871 | −0.000822 | −0.000961 | −0.000783 |
| | | (−1.44) | (−1.34) | (−1.57) | (−1.27) |
| Female share | 0.000152 | 0.000407 | 0.000207 | 0.000131 | 0.0000781 |
| | (0.20) | (0.52) | (0.26) | (0.16) | (0.10) |
| College share | 0.000808 | 0.000419 | 0.000563 | 0.00136 | 0.000282 |
| | (0.58) | (0.29) | (0.36) | (0.89) | (0.18) |
| High school share | −0.00114 | −0.000878 | −0.000129 | 0.000499 | 0.000791 |
| | (−0.50) | (−0.38) | (−0.05) | (0.21) | (0.33) |
| Non-white share | −0.000418 | −0.000536 | −0.000877 | −0.000595 | −0.00102 |
| | (−0.11) | (−0.14) | (−0.22) | (−0.15) | (−0.26) |
| Married share | −0.00478 | −0.00375 | −0.00189 | −0.000950 | −0.00167 |
| | (−1.00) | (−0.78) | (−0.37) | (−0.19) | (−0.33) |
| Mean age | −0.00000104 | −0.00000499 | −0.00000580 | −0.0000103 | −0.00000498 |
| | (−0.01) | (−0.07) | (−0.08) | (−0.13) | (−0.07) |
| Mean # children | 0.000758 | 0.000317 | 0.0000537 | 0.00000976 | −0.0000621 |
| | (0.36) | (0.15) | (0.02) | (0.00) | (−0.03) |
| Order of 1980 wage poly. | 0 | 0 | 3 | 3 | 3 |
| $N = 315$ | | | | | |

Notes: Demographic variables are occupation-level means of the share of workers in an occupation with a college/high-school degree, the share of workers in an occupation who are non-white, the share of workers in an occupation who are married, the share of female workers in an occupation, the mean age of workers in an occupation, and the mean number of children of workers in an occupation. t-statistics are in parentheses. Significance levels are: *** 1%, ** 5%, * 10%.

[a] Complex occupations are defined as those above the 50th percentile (column (iv)) or above the 66th percentile (column (v)) of the complexity index.

Source: Caines et al. (2017a)

- No significant effects on occupational employment share changes; does not support “job polarization”due to RTBTC/automation

# Take-aways

- Conditional on task complexity, wage differences between routine and non-routine jobs are not significant
- Occupations with a high measure of task complexity had higher wages and larger wage- and employment-growth than simple occupations
- Reallocation from simple occupations to complex ones over time
- Wages and wage growth in simple routine- and non-routine occupations not statistically different
- RTBTC (via automation of middle-wage occupations) does not explain wage/job polarization

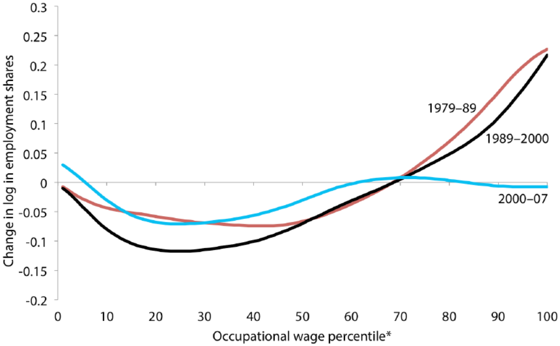
# Robustness Check: “Job Polarization” (Mishel et al., 2013)

- CPS-ORG data to “test” Acemoglu and Autor (2011) job “polarization” finding (from decennial Census, ACS data)
- CPS-ORG: smaller sample sizes, BUT yearly data and more accurate hourly wage data (occupations ranked wrt. 1979 mean wage)
- Major changes in occupation coding (1982-1983, 2002-2003) difficult to bridge, lead to non-trivial employment share series breaks
- “Absolute” job polarization: employment share growth at top, bottom of (occupational) distribution w/ losses in middle
- “Relative” job polarization: U-shaped growth across distribution (i.e., at top, bottom wrt. middle)

# Findings

FIGURE E

**Replication of key job polarization figure using CPS-ORG data adjusted for occupation coding breaks in 1982/1983 and 2002/2003, 1979–89, 1989–2000, 2000–07**




*Ranked by 1979 occupational mean wage.

**Source:** Authors' analysis of Current Population Survey Outgoing Rotation Group microdata

Source: Mishel et al. (2013)

# Interpretation

- 1980s: relative job polarization, less job loss for bottom than middle (as opposed to monotonic increases in Acemoglu and Autor (2011))
- 1990s: replicates Acemoglu and Autor (2011) (no "absolute" polarization)
- 2000-2007: of bottom half, only first five pctiles saw employment share growth (as opposed to much more employment growth at bottom in Acemoglu and Autor (2011)); little or no employment expansion of occupations for upper half
- Key insight: job polarization no longer a factor explaining US inequality trends in 2000s

# Issues (1): Occupational Coding Breaks

- Strategy: replace employment share change over break yrs. w/ avg. change of 2 yrs. on either side of break
- 1982-1983: masks the decline in middle jobs in 1980s (find job polarization in 1980s while Acemoglu and Autor (2011) do not)
- 2002-2003: leads to overstatement of bottom job growth in 2000–2007 period in Acemoglu and Autor (2011)
- 2002/2003: removing break shows more modest growth in bottom during 2000–2007 wrt. Acemoglu and Autor (2011)

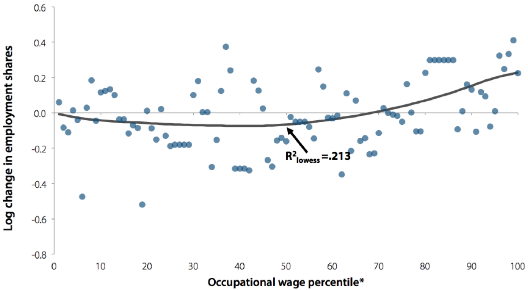
# Issues (2): Oversmoothed Results in Literature

- Variation of employment shifts across detailed occupations obscured by locally-weighted smoothing regression lines in Acemoglu and Autor (2011), etc.
- Reproduce Figure E, w/ scale wide enough to fit unsmoothed log employment share changes at each pctile
- Key insight: literature implicitly differencing potentially non-well-estimated lines (so findings possibly subject to sizeable error margins)

# Non-smoothed Results (1)

**FIGURE FA**

**Change in log employment shares, by occupational wage percentile, 1979–1989**



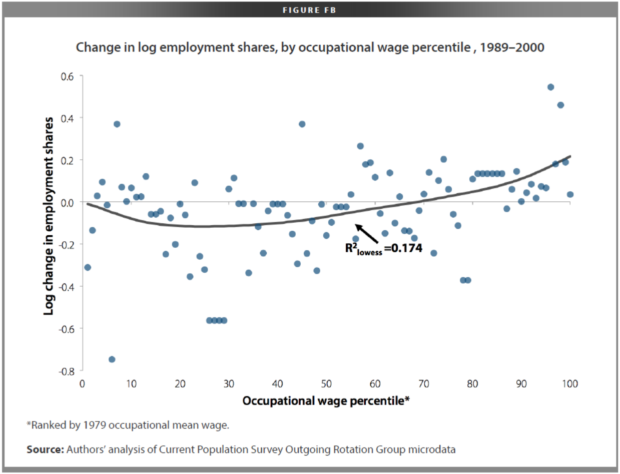

*Ranked by 1979 occupational mean wage.

**Note:** Due to discontinuities in employment shares caused by a major occupational coding change between 1982 and 1983, the change in log employment share between 1982 and 1983 was replaced by the average change of 1980–1981, 1981–1982, 1983–1984, and 1984–1985.

**Source:** Authors' analysis of Current Population Survey Outgoing Rotation Group microdata

Source: Mishel et al. (2013)

# Non-smoothed Results (2)

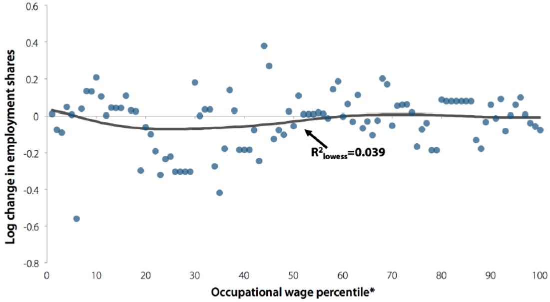



Source: Mishel et al. (2013)

# Non-smoothed Results (3)

FIGURE FC

Change in log employment shares, by occupational wage percentile, 2000–2007




*Ranked by 1979 occupational mean wage.

**Note:** Due to discontinuities in employment shares caused by a major occupational coding change between 2002 and 2003, the change in log employment share between 2002 and 2003 was replaced by the average change of 2000–2001, 2001–2002, 2003–2004, and 2004–2005.

**Source:** Authors' analysis of Current Population Survey Outgoing Rotation Group microdata

Source: Mishel et al. (2013)

# Alternative Explanations of Rising Inequality

- Literature explored factors in addition to SBTC/TBTC (though latter generally deemed more relevant/important)
- Rise of "superstar" individuals (CEOs, athletes, entertainers) w/ abnormally high returns to their skills: Rosen (1981) and related literature (Terviö, 2009; Pallais, 2014)
- Organizational change affecting skill demand (Acemoglu, 1999; Beaudry and Green, 2003; Ann et al., 2004; Caroli and Van Reenen, 2001; Bresnahan et al., 2002; Becker and Murphy, 1992), Dessain and Santos (2008))
- International Trade (Autor and Dorn, 2013; Acemoglu et al., 2016)
- Migration (Borjas, 1995; McKenzie and Rapoport, 2007)

# Conclusion

- SBTC important in explaining selected labor market outcome disparities (to an extent); "task approach"/TBTC as an additional framework
- Key takeaway from this literature: impacts on outcomes (wages, employment) highly dependent upon (labor demand responses to) technological shocks
- Open Questions:
  - What is skill/task (demand)? How to classify skills/tasks?
  - How robust are the (wage/job) "polarization" findings?
  - What explains "polarization" (SBTC/RTBTC/CTBTC/other factors)?

# RESERVE SLIDES

# Skill Types in Deming and Kahn (2018)

Table 1
Description of Job Skills

| Job Skills | Keywords and Phrases |
|---|---|
| Cognitive | Problem solving, research, analytical, critical thinking, math, statistics |
| Social | Communication, teamwork, collaboration, negotiation, presentation |
| Character | Organized, detail oriented, multitasking, time management, meeting deadlines, energetic |
| Writing | Writing |
| Customer service | Customer, sales, client, patient |
| Project management | Project management |
| People management | Supervisory, leadership, management (not project), mentoring, staff |
| Financial | Budgeting, accounting, finance, cost |
| Computer (general) | Computer, spreadsheets, common software (e.g., Microsoft Excel, PowerPoint) |
| Software (specific) | Programming language or specialized software (e.g., Java, SQL, Python) |

Source: Deming and Kahn (2018)

- Coding based on keywords from more than 10,000 fields in BG data (include if min. one keyword listed per ad: is this reasonable/skill demand?)
- Mutually exclusive but not collectively exhaustive (e.g., "quick learner" hard to classify)
- Use literature for cognitive (Autor et al., 2003), social (Deming, 2017), character (Heckman and Kautz, 2012) classifications + relevance/listing frequency for rest

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# Skills Model Extensions: Brief Literature Review

- Multidimensionality of skills potentially important (Lise and Postel-Vinay, 2020)
- Returns to given skill "types", e.g. social skills (Deming, 2017)
- (Early-life) skill formation improves adult outcomes (Kautz et al., 2014; Orrell, 2018)
- Effects on policy of demand for given skills (e.g., Monras (2019) showing minimum wage increases more likely when low-skill employment rising)

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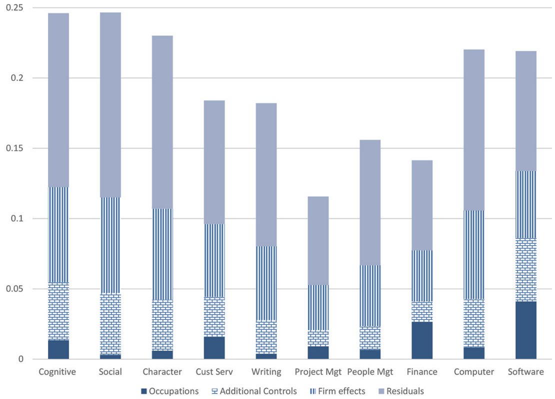
# Variation in Skill Demand Explained by Ad Characteristics




Source: Deming and Kahn (2018)

- Variances of fitted values from regression of dummy for skill inclusion in ad on occupation/MSA/firm FEs, controls; sample limited to firms w/ min. 10 ads in 2 MSAs/occupations
- Large differences b/w firms in skill requirement propensity (approx. 30% of variance; unexplained variation at 50% total)

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# Examples of Tasks, by Type

| | Routine | Non-routine |
|---|---|---|
| Cognitive/Analytic | Solving complex mathematics | Forming or testing hypotheses |
| Manual | Repetitive assembly | Driving through traffic |

Source: Autor et al. (2003); Deming (2017)

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# Occupation List and Complexity/Routineness Percentiles

**Table 2**
Comparison of complexity and routinization.

| Occupation title | Routine index percentile | Complexity index percentile |
|---|---|---|
| | Routinizable occupations with high complex content | |
| Financial managers | 82.825 | 96.109 |
| Real estate sales occupations | 87.416 | 66.033 |
| Accountants and auditors | 95.502 | 78.977 |
| Insurance underwriters | 95.976 | 65.348 |
| Statistical clerks | 93.661 | 93.177 |
| Clinical laboratory technologist and technicians | 74.922 | 73.236 |
| Other financial specialists | 77.201 | 75.251 |
| | Non-routinizable occupations with low complex content | |
| Waiters and waitresses | 12.038 | 3.617 |
| Baggage porters, bellhops and concierges | 9.357 | 26.968 |
| Recreation facility attendants | 27.036 | 11.736 |
| Taxi cab drivers and chauffeurs | 5.054 | 28.085 |
| Personal service occupations | 26.624 | 30.395 |
| Door-to-door sales, street sales, and news vendors | 26.855 | 6.419 |
| Bus drivers | 3.775 | 12.672 |

Notes: The table reports values of the routine and complexity indices for a selection of occupations. The index values are converted to percentiles of the occupation-level distribution. See Sections 2.2 and 2.3 for construction of the routine index and the complexity index.

Source: Caines et al. (2017a)

- O*NET-SOC occupations mapped into Census occupation codes
- Occupations classified as “simple” if below 66th pctile of complexity index (“complex” otherwise)

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# Complexity, routineness, wages, and employment

**Table 3**
Complexity, routineness, wages, and employment.

| | | $\log(wage_{1980})$ | $\log(wage_{2005})$ | $\Delta \log(wage)$ | Employment share 1980 | Employment share 2005 | % Employment change |
|---|---|---|---|---|---|---|---|
| simple | routine | 1.925 | 2.041 | 0.116 | 0.188 | 0.169 | −0.098 |
| | nonroutine | 1.959 | 2.071 | 0.112 | 0.466 | 0.426 | −0.086 |
| complex | | 2.304 | 2.663 | 0.357 | 0.346 | 0.405 | 0.170 |

Notes: Wage and employment data taken from 1980 5% sample of the US Census and the 2005 ACS. Sample restricted to non-institutionalized males aged 16–64 in the mainland United States. Complex occupations defined as those whose complexity index is above the 66th percentile in the occupation-level complexity distribution. All other occupations are defined as simple.

Source: Caines et al. (2017a)

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# Task Complexity and Group[1]/Occupational Wage Growth

**Table 8**
Group-level wage growth regression.

| Dependent variable: change in log wages 1980–2005 | | | |
|---|---|---|---|
| Independent variable | (i) | (ii) | (iii) |
| Complexity index | 0.258*** | 0.273*** | 0.349*** |
| | (10.98) | (10.02) | (12.59) |
| Routine index | | 0.0427 | 0.0440 |
| | | (1.36) | (1.49) |
| Order of 1980 wage poly. | 0 | 0 | 3 |
| $N = 15142$ | | | |

Notes: The table reports results when occupation-level data is disaggregated to occupation × gender × education × race × age cells (see section 7) for discussion. Regressions include gender × education × race × age fixed effects. Standard errors clustered at the occupation level. t-statistics are in parentheses. Significance levels are: *** 1%, ** 5%, * 10%.

**Table 9**
Occupation-level wage growth regression by 1980 wage tercile.

| Dependent variable: change in log wages 1980–2005 | | | |
|---|---|---|---|
| Independent variable | First tercile (i) | Second tercile (ii) | Third tercile (iii) |
| Complexity index | 0.553*** | 0.490*** | 0.624*** |
| | (8.35) | (7.92) | (5.43) |
| Routine index | −0.0327 | −0.0409 | 0.131* |
| | (−0.70) | (−0.88) | (1.90) |
| Order of 1980 wage poly. | 3 | 3 | 3 |
| $N$ | 112 | 108 | 90 |

Notes: The table reports results for occupation-level regressions run for different terciles of the 1980 occupational wage distribution. t-statistics are in parentheses. Significance levels are: *** 1%, ** 5%, * 10%.

Source: Caines et al. (2017a)

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[1] demographic groups (men, women used as proxy for panel data w/ different cohorts): gender, education, race and age; 4 categories for education: i) <HS; ii) HS; iii) some College; and iv) College; 4 categories for age: i) 16-28; ii) 29-40; iii) 41-52; and iv) 53-64; 2 categories for race (white, non-white). For each occupation-demographic cell (total of 15,142 cells): computed 1980-2005 mean wage/total employment changes using 1980 5% Census and 2005 ACS.

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