Accounting for Changes in Between-Group Inequality

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Determinants of Changes in Relative Demand

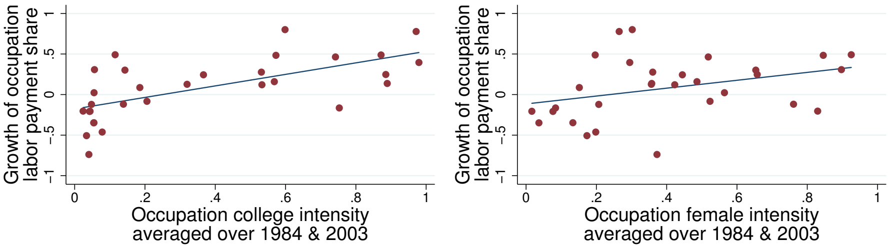
- Pronounced changes in between-group inequality in U.S., e.g.,
  - more educated workers relative to less educated workers
  - women relative to men
- Voluminous literature—following Katz and Murphy (1992)—studying how changes in relative supply and demand for labor groups shape relative wages $\Longrightarrow$ large changes in relative demand
- Changes in relative demand have been linked to, e.g.,
  - computerization (or a reduction in price of equipment more generally)
    - e.g., Krusell et al. (00), Acemoglu (02), Autor and Dorn (13), Beaudry and Lewis (14)
  - changes in relative productivity or demand across occupations or sectors (driven by structural transformation, offshoring, international trade...)
    - e.g., Autor et al. (03), Grossman and Rossi-Hansberg (08), Buera et al. (15)

Computerization

		1984	1989	1993	1997	2003
All		27.4	40.1	49.8	53.3	57.8
Education	College	45.5	62.5	73.4	79.8	85.7
	Non-college	22.1	32.7	41.0	43.7	45.3
Gender	Female	32.8	47.6	57.3	61.3	65.1
	Male	23.6	34.5	43.9	47.0	52.1

- Computer use rises over time
- More educated (female) use computers more than less educated (male)

Changes across occupations



- The occupations with larger growth in total payments to labor are those that are, on average, more intensive in more educated and female workers

Decomposing Changes in Relative Wages

- Assignment framework building on Eaton and Kortum (2002), Hsieh et al. (2013), and Lagakos and Waugh (2013)
  - many groups of workers (in empirics: 30 education-gender-age groups)
  - many occupations (in empirics: 30 e.g. executives, technicians)
  - extended to incorporate equipment (in empirics: computers vs. other)
- Changes in relative wages across worker groups are shaped by shocks to
  - labor composition (relative supply of labor groups)
  - occupation shifters (combo of changes in demand and productivity of occs)
  - equipment productivity (combo of changes in cost/productivity of equipment)
  - labor productivity (combo of factors affecting productivity of worker groups, independent of equipment and occupations)
- Model's implications for relative wages nest those of workhorse macro models, e.g. Katz and Murphy (1992) and Krusell et al. (2000)
- Use model to perform aggregate counterfactuals to quantify the impact on between-group inequality of the four shocks above

Comparative Advantage

- Impact of shocks on inequality shaped by comparative advantage
- Consider impact of computerization
- A labor group may use computers intensively for two reasons
  - has direct comparative advantage (CA) with computers
    - uses computers relatively more within an occupation
    - computerization increases wages of these worker groups
    - this is the case for more educated workers
  - has direct CA in occupations in which computers also have direct CA
    - uses computers as intensively as any other labor group within an occupation
    - computerization may increase or decrease wages of these worker groups
    - this is the case for female workers
- Measuring comparative advantage btw worker groups, equipment types, occupations a key ingredient in quantitative analysis

Preview of the Results: 1984-2003

- Using data on
  - allocations of workers to equipment types and occupations, and
  - wages,

  decompose changes in between-group inequality

- Computerization $\Rightarrow$ majority of rise in between-education-group inequality at high and low levels of education aggregation ($\sim$ 60% for skill premium)
- Occupation shifters and computerization $\Rightarrow$ $\sim$ 80% of rise in skill premium
  - Contrasts with most previous results attributing rise in skill premium largely to unobservables; e.g. Bound et al. (1992) and Lee and Wolpin (2010)

- Occupation shifters, computerization and labor productivity all important for fall in gender gap

- Quantify impact of trade in equipment goods for different trade elasticities

Relation to a large literature

- Capital-skill (or group) complementarity
  - Krusell et al. (2000) use aggregate production function
  - Lee and Wolpin (2010) use sector-level production function
  - We rely on detailed data on computer usage across workers
  - Results robust to allowing for time trends; see e.g. Acemoglu (2002)
- Role of changes in relative demand across sectors/occupations
  - Shift-share analysis; e.g. Katz and Murphy (1992)
    - decomposes changes in wage bill shares
    - but labor supply moves much more than wages
  - Roy-type model; e.g. Hsieh et al. (2013)
    - equipment productivity drives substantial reallocation
- Equipment trade and inequality
  - Previous literature built on aggregate production function; e.g. Burstein et al. (2013) and Parro (2013)

Outline

- Model
  - Without sectors and without international trade
  - Equilibrium in changes
  - Intuition
- Decomposing Changes in Relative Wages
  - Describing the data
  - Factor allocation and comparative advantage
  - Measuring changes in equipment and occupation shifters
  - Estimation of parameters
- Results
- Robustness
- International trade
- Conclusion

MODEL

Environment

- Static environment with a unique final good
- Economy is closed
- All markets are competitive
- CES technology mapping the services from occupations to the final good

$$Y_t = \left(\sum_{\omega} \mu_t(\omega)^{\frac{1}{\rho}} Y_t(\omega)^{\frac{\rho-1}{\rho}} \right)^{\frac{\rho}{\rho-1}}, \qquad \rho > 0$$

- The final good may be used for consumption or to produce equipment goods

$$C_t + \sum_{\kappa} p_t(\kappa) Y_t(\kappa) = Y_t$$

Occupation Production Function

- There is a continuum of workers $z \in \mathcal{Z}_t$ who supply labor inelastically
- All workers have an identical homothetic utility function increasing in C_t
- Workers are divided into labor groups, indexed by λ
- The output of a worker $z \in \mathcal{Z}_t(\lambda)$ who uses k_t units of equipment κ in the production of occupation ω is

$$[T_t(\lambda, \kappa, \omega) \times \epsilon_t(z) \times \varepsilon_t(z, \kappa, \omega)]^{1-\alpha} \times k_t(\kappa)^\alpha$$

  subject to two restrictions:

  1. $\epsilon_t(z)$ independent of $\varepsilon_t(z, \kappa, \omega)$
  2. $\varepsilon_t(z, \kappa, \omega) \sim$ Fréchet : $\quad G(\varepsilon) = \exp(-\varepsilon^{-\theta}), \quad \theta > 1$

- Fréchet analytically tractable and provides reasonable approximation of observed wage distribution; e.g., Saez (2001) and figures below

Occupation Production Function

$$[T_t(\lambda, \kappa, \omega) \times \epsilon_t(z) \times \varepsilon_t(z, \kappa, \omega)]^{1-\alpha} \times k_t(\kappa)^{\alpha}$$

- Cobb-Douglas production function at the level of occupation
  - When $\rho > 1$, employment grows in computer-intensive occupations
- Even though strong restrictions are imposed on the occupation production function, aggregate implications for wages nest those of
  - *canonical model*; e.g. Katz and Murphy (1992)
  - capital-skill complementarity model; e.g. Krusell et al. (2000)

Partial Equilibrium

- Given price of each occupation, $p_t(\omega)$, each worker $z \in \mathcal{Z}_t(\lambda)$ chooses
  - a type of equipment κ and an occupation ω; and,
  - given the choice (κ, ω), the quantity of equipment k
- The probability that a worker $z \in \mathcal{Z}_t(\lambda)$ chooses the pair (κ, ω) is

$$\pi_t(\lambda, \kappa, \omega) = \frac{\left[p_t(\kappa)^{\frac{-\alpha}{1-\alpha}} p_t(\omega)^{\frac{1}{1-\alpha}} T_t(\lambda, \kappa, \omega)\right]^\theta}{\sum_{\kappa', \omega'} \left[p_t(\kappa')^{\frac{-\alpha}{1-\alpha}} p_t(\omega')^{\frac{1}{1-\alpha}} T_t(\lambda, \kappa', \omega')\right]^\theta}$$

Alternative decentralization

Partial Equilibrium: Factor Allocation and Wages

- Comparative advantage (CA) shapes factor allocation
- As an example

$$\frac{T_t(\lambda, \kappa, \omega)}{T_t(\lambda, \kappa', \omega)} > \frac{T_t(\lambda', \kappa, \omega)}{T_t(\lambda', \kappa', \omega)} \Leftrightarrow \frac{\pi_t(\lambda, \kappa, \omega)}{\pi_t(\lambda, \kappa', \omega)} > \frac{\pi_t(\lambda', \kappa, \omega)}{\pi_t(\lambda', \kappa', \omega)}$$

- Similarly for the other two types of comparative advantage
- Implication: use data on factor allocation to measure CA

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- Average wage of λ workers is

$$w_t(\lambda) = \bar{\alpha}\gamma\left(\lambda\right)\left(\sum_{\kappa,\omega}\left(T_t(\lambda,\kappa,\omega)p_t(\kappa)^{\frac{-\alpha}{1-\alpha}}p_t\left(\omega\right)^{\frac{1}{1-\alpha}}\right)^{\theta}\right)^{1/\theta}$$

where $\bar{\alpha}$ and $\gamma(\lambda)$ are constants

Discussion and between-within decomposition

General Equilibrium

- Occupation prices $p_t(\omega)$ must be such that total expenditure in occupation ω is equal to total revenue earned by all factors employed in occupation ω:

$$\mu_t(\omega) p_t(\omega)^{1-\rho} E_t = \frac{1}{1-\alpha} \zeta_t(\omega)$$

where $\zeta_t(\omega)$ is total income of workers employed in occupation ω,

$$\zeta_t(\omega) = \sum_{\lambda,\kappa} w_t(\lambda) L_t(\lambda) \pi_t(\lambda, \kappa, \omega),$$

and E_t is total income

Decomposing Changes in Relative Wages

- Goal is to decompose observed changes in relative average wages between any two labor groups between two periods t_0 and t_1
- In baseline impose (generalize in robustness)

$$T_t(\lambda,\kappa,\omega) = T_t(\lambda)\,T_t(\kappa)\,T_t(\omega)\,T(\lambda,\kappa,\omega)$$

to decompose wage changes into four channels:

  - labor composition, $L_t(\lambda)$;
  - combination of productivity, $T_t(\kappa)$, and production cost, $p_t(\kappa)$, of equipment:

$$q_t(\kappa) \equiv p_t(\kappa)^{\frac{-\alpha}{1-\alpha}}\,T_t(\kappa)$$

  - combination of productivity, $T_t(\omega)$, and demand, $\mu_t(\omega)$, for occupations:

$$a_t(\omega) \equiv \mu_t(\omega)\,T_t(\omega)^{(1-\alpha)(\rho-1)}$$

  - labor productivity, $T_t(\lambda)$

System in Changes

- Denoting by $\hat{x} \equiv x_{t_1}/x_{t_0}$ for any variable x, we have

$$\hat{w}(\lambda) = \hat{T}(\lambda)\left[\sum_{\kappa,\omega}\left(\hat{q}\left(\omega\right)\hat{q}(\kappa)\right)^{\theta}\pi_{t_0}(\lambda,\kappa,\omega)\right]^{1/\theta}$$

where $q_t\left(\omega\right) \equiv p_t(\omega)^{1/(1-\alpha)}T_t(\omega)$

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where $q_t(\omega) \equiv p_t(\omega)^{1/(1-\alpha)}T_t(\omega)$ determined by system of equations

$$\hat{\pi}(\lambda,\kappa,\omega) = \frac{\left(\hat{q}(\omega)\hat{q}(\kappa)\right)^{\theta}}{\sum_{\kappa',\omega'}\left(\hat{q}(\omega')\hat{q}(\kappa')\right)^{\theta}\pi_{t_0}(\lambda,\kappa',\omega')}$$

$$\hat{a}(\omega)\hat{q}(\omega)^{(1-\alpha)(1-\rho)}\hat{E} = \frac{1}{\zeta_{t_0}(\omega)}\sum_{\lambda,\kappa} w_{t_0}(\lambda)L_{t_0}(\lambda)\pi_{t_0}(\lambda,\kappa,\omega)\hat{w}(\lambda)\hat{L}(\lambda)\hat{\pi}(\lambda,\kappa,\omega)$$

Key equation

$$\hat{w}(\lambda) = \hat{T}(\lambda) \left[\sum_{\kappa,\omega} \left(\hat{q}\left(\omega\right) \hat{q}(\kappa) \right)^{\theta} \pi_{t_0}(\lambda, \kappa, \omega) \right]^{1/\theta}$$

- Taking first-order approx of wage equation, micro-found regression model introduced in Acemoglu and Autor (2011)

$$\log \hat{w}(\lambda) = \log \hat{T}(\lambda) + \sum_{\kappa,\omega} \pi_{t_0}(\lambda, \kappa, \omega) \left(\log \hat{q}\left(\omega\right) + \log \hat{q}(\kappa) \right)$$

- Changes in $a_t(\omega)$ and $L_t(\lambda)$ affect wages only in GE through $q_t\left(\omega\right)$

Intuition (I)

$$\hat{w}(\lambda) = \hat{T}(\lambda)\left[\sum_{\kappa,\omega}\left(\hat{q}\left(\omega\right)\hat{q}(\kappa)\right)^{\theta}\pi_{t_0}(\lambda,\kappa,\omega)\right]^{1/\theta}$$

- Changes in $a_t(\omega)$ and $L_t(\lambda)$, in limiting case with $\alpha = 0$, $T\left(\lambda,\omega\right)$ log-supermodular, no idiosyncratic productivity: Costinot and Vogel (2010)
- For instance: $\uparrow\ a_t(\omega)\ \Rightarrow\uparrow\ q_t(\omega)\ \Rightarrow\uparrow$ relative wage of labor groups disproportionately employed in ω
  - Higher ρ weakens this mechanism

Intuition (II)

$$\hat{w}(\lambda) = \hat{T}(\lambda)\left[\sum_{\kappa,\omega}\left(\hat{q}\left(\omega\right)\hat{q}(\kappa)\right)^{\theta}\pi_{t_0}(\lambda,\kappa,\omega)\right]^{1/\theta}$$

- Equipment: consider $\hat{q}(\kappa) > 1$ for some κ
  - raises wages of worker groups that use κ intensively
  - reduces prices in occupations in which κ is used intensively, lowering relative wages of worker groups intensively employed in these occupations

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- Equipment: consider $\hat{q}(\kappa) > 1$ for some κ
  - raises wages of worker groups that use κ intensively
  - reduces prices in occupations in which κ is used intensively, lowering relative wages of worker groups intensively employed in these occupations
- Case 1. If CA is only between workers and equipment:
  - no change in relative occupation prices
- Case 2. If CA is only btw workers and occupations and btw equipment and occupations:
  - if occs. gross substitutes ($\rho > 1$), relative wages of worker groups intensively employed in κ-intensive occs. rise as does employment in these occupations
  - both effects exactly cancel in the Cobb-Douglas case

DECOMPOSING CHANGES IN RELATIVE WAGES

Our approach

- From system in changes, need
  - Measures of variables in period t_0

$$\pi_{t_0}(\lambda, \kappa, \omega), w_{t_0}(\lambda), L_{t_0}(\lambda), \zeta_{t_0}(\omega)$$

  - Measures of shocks

$$\frac{\hat{L}(\lambda)}{\hat{L}(\lambda_1)}, \frac{\hat{T}(\lambda)}{\hat{T}(\lambda_1)}, \frac{\hat{q}(\kappa)^\theta}{\hat{q}(\kappa_1)^\theta}, \frac{\hat{a}(\omega)}{\hat{a}(\omega_1)}$$

  - Estimates of parameters

$$\rho, \alpha, \theta$$

Data

- Measure $w_t(\lambda)$ and $L_t(\lambda)$ as average hourly wages and hours worked for group λ using Combined CPS May, Outgoing Rotation Group

- Measure $\pi_t(\lambda, \kappa, \omega)$ using October CPS in 1984, 1989, 1993, 1997, and 2003

- In these years, October CPS asks if respondent uses computers at work
  - refers only to "direct" or "hands on" use of a computer
  - defines computer as a machine with typewriter-like keyboards

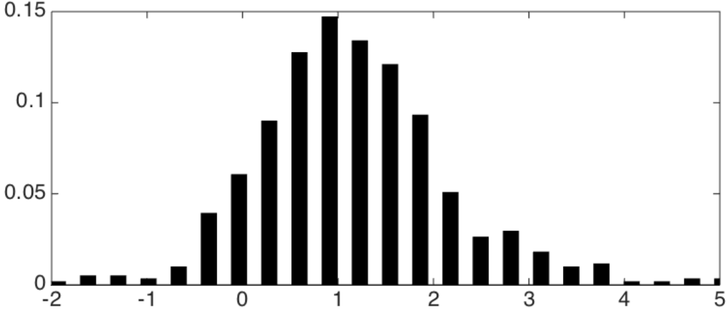
- $\pi_t(\lambda, \kappa', \omega)$ is the share of hours worked by λ who are employed in occupation ω and use a computer, κ', at work, relative to the total hours worked by λ

  - Narrow view of computerization (not capture automation of assembly lines)
  - Not using data on non-computer allocation
  - Computer-use a zero-one variable

Factor Allocation: Education - Computer

- More educated workers (λ' and λ are CLG and HSG of the same gender) use computers (κ') relatively more within occupations

$$\log \frac{\pi_t(\lambda', \kappa', \omega)}{\pi_t(\lambda', \kappa, \omega)} - \log \frac{\pi_t(\lambda, \kappa', \omega)}{\pi_t(\lambda, \kappa, \omega)}$$

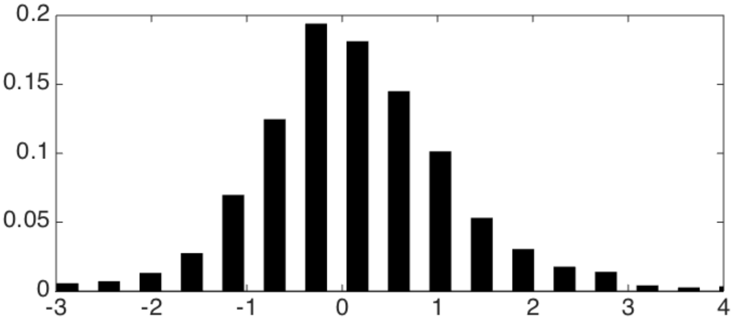


Histogram across all time periods, occupations, and genders x ages (5 x 30 x 6)

Factor Allocation: Gender - Computer

- No clear difference between female (λ') and male (λ) workers' computer (κ') usage within occupations

$$\log \frac{\pi_t(\lambda', \kappa', \omega)}{\pi_t(\lambda', \kappa, \omega)} - \log \frac{\pi_t(\lambda, \kappa', \omega)}{\pi_t(\lambda, \kappa, \omega)}$$



Histogram across all time periods, occupations, and educations x ages (5 x 30 x 15)

Other Examples

Measuring Shocks: Equipment

- Equipment productivity (to the power θ):

$$\frac{\hat{q}(\kappa)^{\theta}}{\hat{q}(\kappa_1)^{\theta}} = \frac{\hat{\pi}(\lambda, \kappa, \omega)}{\hat{\pi}(\lambda, \kappa_1, \omega)}$$

- Measure positive growth in the equipment shifter corresponding to computers
  - (λ, ω) pairs experience growth in the share of hours worked with computers

Measuring Shocks: Occupation Shifters

- Similar approach to measure transformed occupation prices (to the power θ)

$$\frac{\hat{q}(\omega)^{\theta}}{\hat{q}(\omega_1)^{\theta}} = \frac{\hat{\pi}(\lambda, \kappa, \omega)}{\hat{\pi}(\lambda, \kappa, \omega_1)}$$

which we use to construct occupation shifters once we estimate ρ, α, θ

$$\frac{\hat{a}(\omega)}{\hat{a}(\omega_1)} = \frac{\hat{\zeta}(\omega)}{\hat{\zeta}(\omega_1)} \left(\frac{\hat{q}(\omega)}{\hat{q}(\omega_1)} \right)^{(1-\alpha)(\rho-1)}$$

$\zeta_t(\omega)$ is total payments to labor in ω

  - If $\rho = 1$, measure growth in an occupation shifter if labor payments in that occupation grow relative to total labor payments

Measuring Shocks: Labor Productivity

- Using above measures of $\hat{q}(\kappa)^\theta / \hat{q}(\kappa_1)^\theta$ and $\hat{q}(\omega)^\theta / \hat{q}(\omega_1)^\theta$, construct

$$\hat{s}(\lambda) = \sum_{\kappa,\omega} \frac{\hat{q}(\omega)^\theta}{\hat{q}(\omega_1)^\theta} \frac{\hat{q}(\kappa)^\theta}{\hat{q}(\kappa_1)^\theta} \pi_{t_0}(\lambda, \kappa, \omega)$$

- Together with estimate of θ, measure changes in labor productivity

$$\frac{\hat{T}(\lambda)}{\hat{T}(\lambda_1)} = \frac{\hat{w}(\lambda)}{\hat{w}(\lambda_1)} \left(\frac{\hat{s}(\lambda_1)}{\hat{s}(\lambda)} \right)^{1/\theta}$$

Parameters to Estimate

- Parameters to calibrate and estimate
  - α: equipment share in Cobb-Douglas task production
  - θ: dispersion of $\varepsilon(z, \kappa, \omega)$
  - ρ: elasticity of substitution across occupations in production of final good
- We set $\alpha = 0.24$, consistent with estimates in, e.g., Burstein et al. (2013)
  - Calibrating in our model is equivalent
- We jointly estimate θ and ρ

Estimation of θ and ρ

- Model generates two estimating equations that jointly identify θ and ρ:

$$\log \hat{w}(\lambda, t) = \varsigma_\theta(t) + \frac{1}{\theta} \log \hat{s}(\lambda, t) + \iota_\theta(\lambda, t)$$

  and

$$\log \hat{\zeta}(\omega, t) = \varsigma_\theta(t) + \frac{(1-\alpha)(1-\rho)}{\theta} \log \frac{\hat{q}(\omega, t)^\theta}{\hat{q}(\omega_1, t)^\theta} + \iota_\rho(\omega, t)$$

  with $\iota_\theta(\lambda, t) \equiv \log \hat{T}(\lambda, t)$ and $\iota_\rho(\omega, t) \equiv \log \hat{a}(\omega, t)$

- To form moment conditions that jointly identify θ and ρ, we use
  - data on $\{\log \hat{w}(\lambda, t)\}$ and $\{\log \hat{\zeta}(\omega, t)\}$
  - measures of $\{\log \hat{s}(\lambda, t)\}$ and $\{\log \hat{q}(\omega, t)^\theta / \hat{q}(\omega_1, t)^\theta\}$

Estimation of θ and ρ

- Our model predicts that, for any given t,

$$ {}_{\lambda}\Big(\log \hat{T}(\lambda, t), \log \hat{s}(\lambda, t) \Big) < 0, $$

$$ cov_{\omega}\Big(\log \hat{a}(\omega, t), \log \frac{\hat{q}(\omega, t)^{\theta}}{\hat{q}(\omega_1, t)^{\theta}} \Big) > 0, $$

and, therefore, our model predicts that a NLS estimator of θ and ρ will yield

  - an estimate of θ that is biased upwards; and
  - an estimate of ρ that is biased downwards

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  and, therefore, our model predicts that a NLS estimator of θ and ρ will yield

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- We use a GMM estimator instead and use as instruments

$$
\chi_{\theta}(\lambda, t) \equiv \log \sum_{\kappa} \frac{\hat{q}(\kappa, t)^{\theta}}{\hat{q}(\kappa_1, t)^{\theta}} \sum_{\omega} \pi_{1984}(\lambda, \kappa, \omega)
$$

$$
\chi_{\rho}(\omega, t) \equiv \log \sum_{\kappa} \frac{\hat{q}(\kappa, t)^{\theta}}{\hat{q}(\kappa_1, t)^{\theta}} \sum_{\lambda} \frac{L_{1984}(\lambda)\, \pi_{1984}(\lambda, \kappa, \omega)}{\sum_{\lambda', \kappa'} L_{1984}(\lambda')\, \pi_{1984}(\lambda', \kappa', \omega)}
$$

Estimation of θ and ρ

- Our benchmark estimates use moment conditions derived under the assumption that

$$\mathbb{E}_\lambda\Big(\log \hat{T}(\lambda, t) \times \chi_\theta (\lambda, t) \Big) = 0,$$
$$\mathbb{E}_\omega\Big(\log \hat{a}(\omega, t) \times \chi_\rho (\omega, t) \Big) = 0.$$

- As a robustness, we also compute GMM estimates that use moment conditions derived under the weaker assumption that

$$\mathbb{E}_\lambda\Big(\log \hat{T}^*(\lambda, t) \times \chi^*_\theta (\lambda, t) \Big) = 0,$$
$$\mathbb{E}_\omega\Big(\log \hat{a}^*(\omega, t) \times \chi^*_\rho (\omega, t) \Big) = 0,$$

where * denotes deviations from a λ- or ω-specific time trend; e.g.

$$\log \hat{T}\left(\lambda, t_0\right) = \beta_\theta\left(\lambda\right) \times \left(t_1 - t_0\right) + \log \hat{T}^*\left(\lambda, t_0\right),$$
$$\log \hat{a}\left(\omega, t_0\right) = \beta_\rho\left(\omega\right) \times \left(t_1 - t_0\right) + \log \hat{a}^*\left(\omega, t_0\right).$$

Estimation of θ and ρ

Estimates:

Estimation Approach	(θ, ρ)	$(s.e.(\theta), s.e.(\rho))$
GMM - Baseline	(1.78, 1.78)	(0.29, 0.35)
GMM - Time Trend	(1.13, 2.00)	(0.32, 0.71)

Estimation of θ and ρ

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GMM - Baseline	(1.78, 1.78)	(0.29, 0.35)
GMM - Time Trend	(1.13, 2.00)	(0.32, 0.71)
NLS	(2.61, 0.21)	(0.57, 0.45)
GMM - Levels	(1.57, 3.27)	(0.14, 1.34)

Additional checks: Estimation relation to literature

- NLS estimates of θ and ρ are higher and lower, respectively, than their GMM estimates, consistent with the predictions of the model
- Estimate (θ, ρ) using equations in levels (instead of time changes) and adding (λ, t) FEs to wage equation and (ω, t) FEs to occupation share equation
- Theory predicts labor supply affects wages only through $\log \hat{s}(\lambda, t)$. Estimate θ using 2SLS adding labor supply: $\theta = 1.84$ and labor supply insignificant

RESULTS

Decomposing Changes in Skill Premium

- Changes in the log of the composition-adjusted skill premium 1984-2003

Data	Labor comp.	Occupation shifters	Equip. prod.	Labor prod.
0.151	-0.114	0.049	0.159	0.056

- Computerization accounts for $\sim 60\%$ of the demand-side forces. Intuition:
  - Computerization raises skill premium through two channels
    1. Strong education-computer comparative advantage
    2. Educated and computers have CA in similar occupations and $\rho > 1$
- Occupation shifters account for $\sim 19\%$. Intuition:
  - Growth of education-intensive occupations (e.g. health assessment) shift-share
- Labor productivity accounts for $\sim 21\%$

Decomposing Changes in Wages by Education Group

- Changes in skill premium aggregate across heterogeneous changes in relative wages between more disaggregated groups

	Data	Labor comp.	Occupation shifters	Equip. prod.	Labor prod.
HS grad / HS dropout	0.037	-0.094	0.022	0.128	-0.060
Some college / HS dropout	0.074	-0.095	0.050	0.231	-0.110
College / HS dropout	0.174	-0.161	0.062	0.296	-0.022
Grad training / HS dropout	0.232	-0.189	0.104	0.310	0.009

- Conclusions for skill premium hold at more disaggregated level
  - computerization central force driving changes in btw education inequality
  - labor productivity plays a relatively small role

Decomposing Changes in Wages by Gender

- Changes in the log of the composition-adjusted gender gap 1984-2003

Data	Labor comp.	Occupation shifters	Equip. prod.	Labor prod.
-0.133	0.042	-0.067	-0.047	-0.061

- Computerization account for $\sim$ 27% of demand-side forces
  - Intuition: women and computers have CA in similar occupations and $\rho > 1$
  - Consistent with local labor mkt empirics: Beaudry and Lewis (2014)
- Occ. shifters account for $\sim$ 38%, driven by contraction in certain male-intensive occupations (e.g. mechanics, machine operators, ...)
- Labor productivity accounts for $\sim$ 35%
  - forces such as discrimination may be important, esp. early in our sample

ROBUSTNESS

Robustness

- Vary values of θ and ρ
- Allow comparative advantage to change over time
- Restrict sources of comparative advantage

Alternative Values for θ and ρ

- $\theta \uparrow \Rightarrow$ relative importance of changes in labor productivity $\uparrow$

$$\log \hat{w}(\lambda, t) = \varsigma_\theta(t) + (1/\theta) \log \hat{s}(\lambda, t) + \log \hat{T}(\lambda, t)$$

- $\rho \uparrow \Rightarrow$ occupation prices less responsive to shocks
  - Less responsive occupation prices reduce effects of labor composition and reduce the indirect effect (on ω prices) of computerization
- ρ also affects measured occupation shifters
  - $\rho \uparrow \Rightarrow$ occupation shifters less biased towards educated workers

	Skill premium				Gender gap			
(θ, ρ)	Labor comp.	Occ. shifters	Equip. prod.	Labor prod.	Labor comp.	Occ. shifters	Equip. prod.	Labor prod.
(1.78, 1.78)	-0.114	0.049	0.159	0.056	0.042	-0.067	-0.047	-0.061
(1.13, 2.00)	-0.126	-0.018	0.272	0.022	0.046	-0.057	-0.092	-0.031

▸ Further intuition for ρ

Changing Comparative Advantage over Time

- Three different cases

$$T_t(\lambda,\kappa,\omega) = \begin{cases} T_{\omega t}(\omega)\,T_{\lambda\kappa t}(\lambda,\kappa)\,T(\lambda,\kappa,\omega) & \text{case 1} \\ T_{\kappa t}(\kappa)\,T_{\lambda\omega t}(\lambda,\omega)\,T(\lambda,\kappa,\omega) & \text{case 2} \\ T_{\lambda t}(\lambda)\,T_{\kappa\omega t}(\kappa,\omega)\,T(\lambda,\kappa,\omega) & \text{case 3} \end{cases}$$

- Results are largely unchanged, holding α, ρ, θ fixed
- Consider, e.g., case 2
  - Measures of labor composition (data), equipment productivity (measured within $\lambda \times \kappa$ pairs) are the same as in baseline
    $\Rightarrow$ Contribution of labor comp., equipment prod. identical to baseline
  - Sum of all changes similar to actual changes in wages
    $\Rightarrow$ Contribution of changes in (λ, ω) shifters must be similar to sum of effects of labor productivity and occupation shifters in baseline

Restricting sources of comparative advantage

- Abstract from equipment CA: $T(\lambda, \kappa_1, \omega) = T(\lambda, \kappa_2, \omega)$
- Similarly abstract from occupation CA: $T(\lambda, \kappa, \omega_i) = T(\lambda, \kappa, \omega_j)$ for all i, j

		Labor comp.	Occupation shifters	Equip. prod.	Labor prod.
Skill premium	Baseline	-0.114	0.049	0.159	0.056
	Only $\lambda \times \kappa$ CA	0	0	0.240	-0.088
	Only $\lambda \times \omega$ CA	-0.114	0.116	0	0.149
Gender gap	Baseline	0.042	-0.067	-0.047	-0.061
	Only $\lambda \times \kappa$ CA	0	0	-0.105	-0.029
	Only $\lambda \times \omega$ CA	0.042	-0.056	0	-0.120

We fix α, ρ, and θ at their baseline values

INTERNATIONAL TRADE

International Trade

- In appendix,
  - show how to incorporate sectors
  - and trade in: (1) equipment, (2) sectors, (3) occupations
- Here, focus exclusively on equipment trade

International Trade in Equipment

Setup

- In open economy, distinguish btw absorption, $D_n(\kappa)$, and production, $Y_n(\kappa)$
- Given iceberg transportation costs for equipment type κ, $d_{ni}(\kappa)$, we have

$$D_n(\kappa) = \left(\sum_i D_{in}(\kappa)^{\frac{\eta(\kappa)-1}{\eta(\kappa)}} \right)^{\frac{\eta(\kappa)}{\eta(\kappa)-1}}$$

$$Y_n(\kappa) = \sum_i d_{ni}(\kappa) D_{ni}(\kappa)$$

- Resource constraint

$$Y_n = C_n + \sum_\kappa p_n(\kappa) Y_n(\kappa)$$

International Trade in Equipment

Moving to autarky

- Equations for $\pi(\lambda, \kappa, \omega)$ and $w(\lambda)$ unchanged
- Absorption price of κ, $p_n(\kappa)$, depends on production prices in all countries

$$p_n(\kappa) = \left[\sum_i p_{in}(\kappa)^{1-\eta(\kappa)} \right]^{\frac{1}{1-\eta(\kappa)}}$$

- In changes

$$\hat{p}_n(\kappa) = \left[\sum_i s_{in}(\kappa) \left(\hat{d}_{in}(\kappa) \hat{p}_{ii}(\kappa) \right)^{1-\eta(\kappa)} \right]^{\frac{1}{1-\eta(\kappa)}}$$

where $s_{in}(\kappa)$ is share of absorption in n from i

- Going to autarky, $\hat{d}_{in}(\kappa) \to \infty$ for all $i \neq n$ implies

$$\hat{p}_n(\kappa) = s_{nn}(\kappa)^{\frac{-1}{\eta(\kappa)-1}} \ \rightarrow \ \hat{q}_n(\kappa) = s_{nn}(\kappa)^{\frac{1}{\eta(\kappa)-1} \frac{\alpha}{1-\alpha}}$$

International Trade in Equipment

Impact of trade in equipment between two time periods

- What are the differential effects of changes in primitives (i.e. worldwide technologies, labor compositions, and trade costs) between periods t_0 and t_1 on wages in country n relative to the effects of the same changes in primitives if country n were a closed economy?

- This counterfactual amounts to moving to autarky at t_0 and again at t_1
- Changes in wages moving to autarky can be evaluated using the closed economy system of equations, where equipment shifters are given by

$$\hat{q}(\kappa) = s_{nn}(\kappa)^{\frac{1}{\eta(\kappa)-1}\frac{\alpha}{1-\alpha}}$$

International Trade in Equipment

Results

Table: Differential effects of changes in primitives btw 1984-2003 on U.S. inequality relative to the effects of the same changes in primitives if the U.S. were a closed economy

	Value of $\eta(\kappa) - 1$		
	1.5	3.5	5.5
Skill premium	0.050	0.021	0.013
HS grad / HS dropout	0.026	0.012	0.008
Some college / HS dropout	0.047	0.021	0.013
College / HS dropout	0.078	0.034	0.021
Grad training / HS dropout	0.080	0.034	0.022
Gender gap	-0.011	-0.005	-0.003

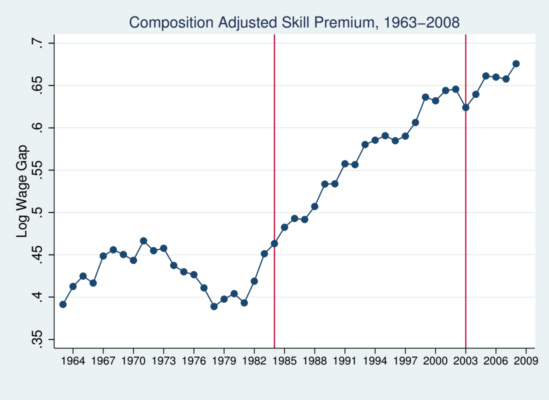
CONCLUSION

Conclusions

- Developed, parameterized framework linking four types of shocks to inequality
- Computerization drives majority of changes in between-education-group inequality in the U.S. between 1984 and 2003
- Computerization + occ. shifters account for $\sim$ 65% of fall in gender gap
- Framework remains tractable
  - Included trade and sectors
  - Further decomposed shocks
- Fruitful avenues for future research include
  - Measuring occupation trade
  - Intra-national trade leveraging regional analyses (e.g. Autor and Dorn 2013)
  - Distribution of income accruing to labor and capital
  - Within-group inequality

APPENDIX

Skill Premium Over Time



- Autor (2014): $\simeq 2/3$ of $\uparrow$ wage dispersion 1980-2005 accounted for by $\uparrow$ post-secondary education premium

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Partial Equilibrium

- An occupation production unit hiring k units of equipment κ and l efficiency units of labor λ earns profit

$$p_t(\omega)k^{\alpha}[T_t(\lambda,\kappa,\omega)l]^{1-\alpha} - p_t(\kappa)k - W_t(\lambda,\kappa,\omega)l$$

  where $W_t(\lambda,\kappa,\omega) =$ wage per efficiency unit of labor λ teamed with κ in ω
- Profit maximizing choice of k and the zero profit condition yield

$$W_t(\lambda,\kappa,\omega) = (1-\alpha)\left(\frac{\alpha}{p_t(\kappa)}\right)^{\frac{\alpha}{1-\alpha}} p_t(\omega)^{\frac{1}{1-\alpha}} T_t(\lambda,\kappa,\omega)$$

  if there is positive entry in (λ,κ,ω)
- Facing wage profile $W_t(\lambda,\kappa,\omega)$, each worker $z \in \mathcal{Z}_t(\lambda)$ chooses (κ,ω) to maximize her labor income, $\varepsilon_t(z,\kappa,\omega)\, W_t(\lambda,\kappa,\omega)$

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Occupations

Executive, administrative, managerial	Health service (e.g. nursing aids)
Management related	Building, grounds cleaning, maintenance
Architect	Child care
Engineer	Administrative support
Life, physical, and social science	Miscellaneous*
Computer and mathematical	Housekeeping, cleaning, laundry
Community and social services	Food preparation and service
Lawyers	Protective service (e.g. police, fire, security)
Education, training, etc...*	Construction
Arts, design, entertainment, sports, media	Mechanics and repairers
Health diagnosing	Agriculture and mining
Health assessment and treating	Handlers, equip. cleaners, helpers, laborers
Technicians and related support	Transportation and material moving
Financial sales and related	Machine operators, assemblers, inspectors
Retail sales	Precision production

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Fréchet Implication For Wage Variation

- Fréchet assumption implies average wages for λ in (κ, ω), denoted $w_t(\lambda, \kappa, \omega)$, does not vary with (κ, ω)
  - This implication is rejected by the data

- Do these differences drive our results?
- We conduct a btw w/in decomposition of changes in $w_t(\lambda)/w_t$

$$\frac{w_t(\lambda)}{w_t} = \sum_{\omega} \frac{w_t(\lambda, \omega)}{w_t} \pi_t(\lambda, \omega)$$

  btw and w/in ω only (b/c insufficient data on wages by κ)
- Model: changes accounted for by changes in w/in component $w_t(\lambda, \omega)/w_t$
- 1984-2003: the median contribution across λ of the w/in component $> 86\%$

- Nevertheless, we include an extension w/ preference shifters giving rise to compensating differentials as in Heckman and Sedlacek (1985)

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Factor Allocation: Other examples

- Can similarly show, e.g.,
  - Women much more likely to work in administrative support relative to in construction, conditional on κ
  - Computers much more likely to be used in administrative support relative to in construction, conditional on λ
- An example of a more general relationship:
  - Women employed in occupations in which all worker groups relatively more likely to use computers

Back

Shift-share analyses

- W/ Cobb-Douglas utility, production functions shift-share analysis structurally decomposes into w/in and btw occ. shifters changes in wage bill shares
  - i.e. changes in $w(\lambda) L(\lambda)$ relative to $\sum_{\lambda'} w(\lambda') L(\lambda')$

- Changes in wage bill shares very different from changes in relative wages when changes in labor composition are large, as they are in the data

- Cobb Douglas utility, production functions
  - preclude "capital-skill complementarity"
  - inconsistent with our estimate of $\rho > 1$

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Intuition for varying ρ

- Computerization doesn't affect income shares across occupations $\iff \rho = 1$
  $\Rightarrow$ computerization only impacts wages through direct CA with computers
- $\rho = 1 \Rightarrow \uparrow$ wages of groups with CA using computers
- $\rho > 1 \Rightarrow \uparrow$ wages of groups with CA in occs. in which computers have CA
- $\rho < 1 \Rightarrow \downarrow$ wages of groups with CA in occs. in which computers have CA

	Skill premium				Gender gap			
ρ	Labor comp.	Occ. shifters	Equip. prod.	Labor prod.	Labor comp.	Occ. shifters	Equip. prod.	Labor prod.
0.1	-0.311	0.491	-0.089	0.032	0.117	-0.273	0.090	-0.046
1	-0.162	0.158	0.102	0.050	0.060	-0.118	-0.014	-0.057
10	-0.028	-0.152	0.260	0.066	0.010	0.028	-0.108	-0.067

Here we vary ρ holding fixed our baseline estimate of $\theta = 1.78$

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Estimation of θ and ρ

Relation to the literature

- Estimation of θ related to two approaches in literature studying impact of worker allocations (across either computers or occupations) on wages

(1) Regress worker wage on characteristics, concurrent computer usage

- See e.g. Krueger (1993)
- Key critique of, e.g., DiNardo and Pishke (1997),
  - endogenous changes in idiosyncratic labor productivity that correlate with changes in labor-group-specific computer usage bias estimates,

does not apply to our approach, which is more closely related to...

(2) Regress changes in labor-group-specific wages on beginning-of-sample measures of labor-group specialization across occupations

- See e.g. Acemoglu and Autor (2011)
- Relative to this, we incorporate interaction of measures of specialization with measures of changes in occupation prices and equipment productivities
  - This is crucial to recover structural parameters required to conduct decompositions and counterfactuals

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Fit of θ using MLE

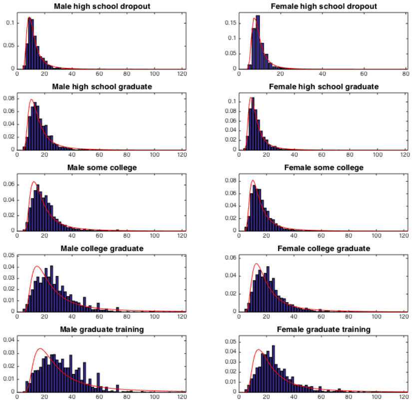

Figure: Empirical and predicted wage distributions for middle-aged workers for year 2003. Predicted distribution incorporates MLE estimates of θ. Back