Engines of Sectoral Labor Productivity Growth

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Motivation

Key fact of modern growth: structural transformation & differences in sectoral labor productivity

- in the US between 1960 and 2010 annual lab. prod. growth was
  - 2.74% in goods
  - 1.66% in low-skilled services
  - 0.90% in high-skilled services
- these growth rates
  - are easy to compute from readily available data
  - but mask important heterogeneity both within and across sectors

Goal of this paper: understand the origins of sectoral labor productivity growth

Sources of sectoral labor productivity differences

1. sectoral differences in the growth of TFP or of labor augmenting technologies $\rightarrow$ tech. change that is biased across sectors
2. differences in capital intensity across sectors
   - capital accumulation has different effects

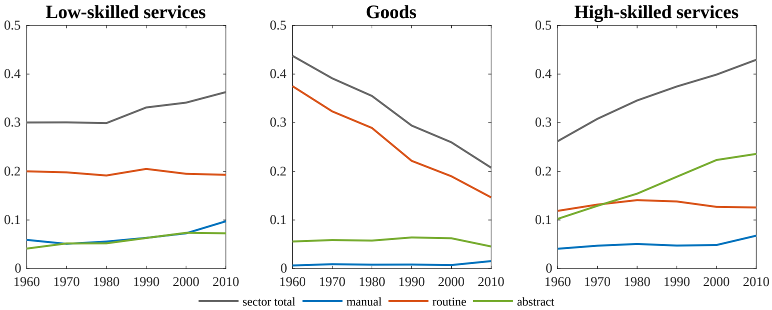
   $\rightarrow$ computer and traditional capital
3. heterogeneity of workers within a sector
   - improvements in the productivity of a subgroup of workers
   - AND reallocations between different groups of workers

   $\rightarrow$ different occupations, performing different tasks
   tech. change that is biased across occupations

Differentiate between occupations

1. since tasks are different, occupations are not perfect substitutes
2. occupations are likely to use different technologies $\rightarrow$ composition changes affects a sector's labor productivity
3. effects of new technologies or other inputs might depend tasks (e.g. ICT substituting routine workers)
4. Acemoglu and Autor (2011): polarization warrants to move beyond canonical (skilled vs. unskilled) models. Bárány and Siegel (2018): polarization started in 1950/1960s.
5. tight connection between changes in sectoral and in occupational employment

Sector-occupation hours worked shares 1960-2010



1. Goods sector most intensive in routine, high-skilled services in abstract occupations
2. Contraction in goods employment due to routine employment; most of rise in high-sk. services due to abstract employment

$\Rightarrow$ important to distinguish between occupations when studying sectoral labor productivity growth

In this paper

we propose a supply side framework to identify the nature of technological change $\rightarrow$ growth accounting

- need a model to quantify technological change biased across factors of production
- assume nested CES function in 5 factors
  - 3 types of labor: manual, routine and abstract
  - 2 types of capital: computer and traditional
- allow for productivity growth to be specific to sector & factor
  - not taking a stance on biases in any way
  - can capture general purpose technologies, sector-specific innovations, task/occupation-biased technological change, ...
- more productivity parameters to identify in this flexible setup, but can pin down all these productivities from the data

In this paper

We quantify the importance

$\rightarrow$ of changing factor inputs

$\rightarrow$ of technological improvements

by calculating sectoral labor productivity growth while holding factor inputs **or** technologies at their 1960 level

We examine labor augmenting technological change further

$\rightarrow$ use a factor model to decompose the Δ in sector-occ technologies into components common to sectors and to occupations

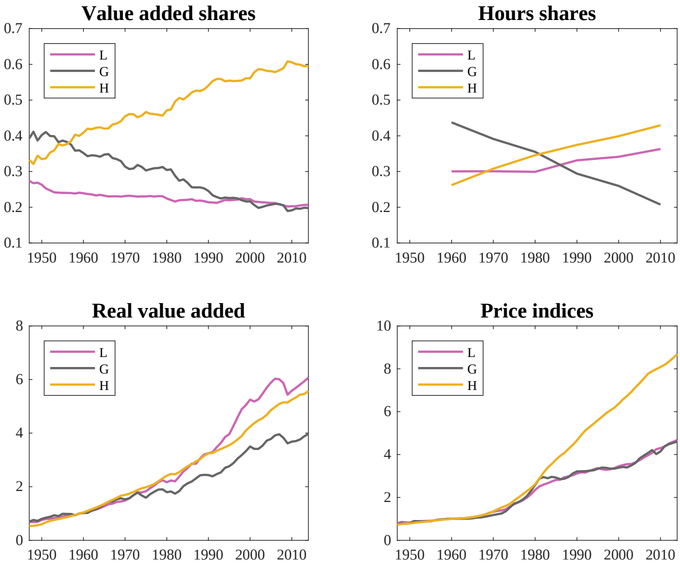
$\rightarrow$ evaluate their role in sectoral labor productivity differences

Related literature

1. structural transformation
   Ngai and Pissarides (2007), Acemoglu and Guerrieri (2008)
2. polarization
   Autor, Katz, and Kearney (2006), Autor and Dorn (2013), Goos and Manning (2007), Goos, Manning, and Salomons (2009, 2014)
3. connection between polarization and structural transformation
   Goos, Manning and Salomons (2014), Duernecker and Herrendorf (2015), Lee and Shin (2015), Bárány and Siegel (2018)
4. biased technological change
   Katz and Murphy (1992), Krusell, Ohanian, Ríos-Rull, and Violante (2000)

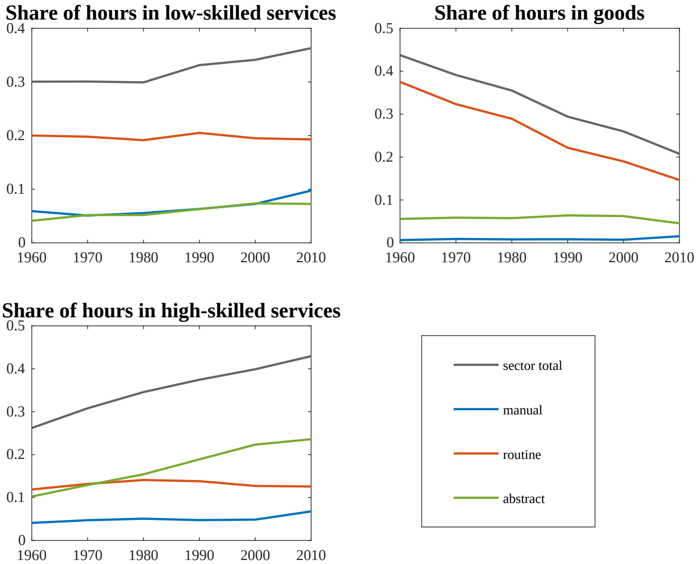
Data on factor use and factor income shares

Structural transformation



Source: Authors' own calculations from BEA, US Census and ACS data ▸ details

Sector-occupation share of hours worked



Source: Authors' own calculations from US Census and ACS data ▸ details

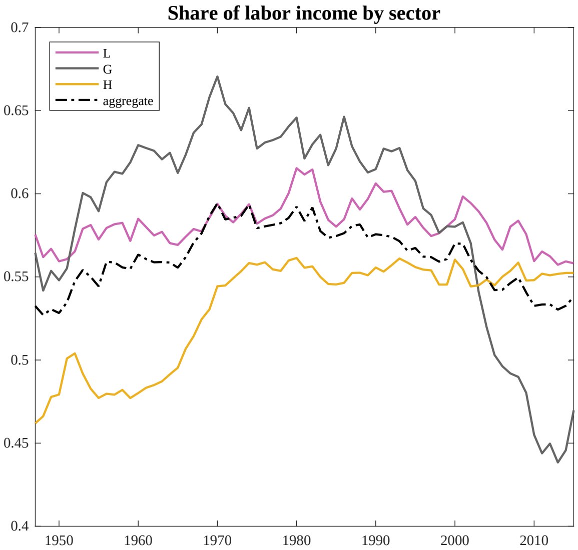
Heterogeneity within and between sectors

1. each sector uses all types of occupations
    - occupations perform different tasks, and are imperfect substitutes in production
    - *polarization* in all sectors: the reallocation of employment (and Δ in wages)
        - away from middle-earning routine occupations
        - towards low-earning manual and high-earning abstract occ
    - main explanation for polarization
        - ICT-induced routinization
        - substitutes for routine tasks, complements abstract tasks

        $\rightarrow$ technological change that is biased across occupations OR

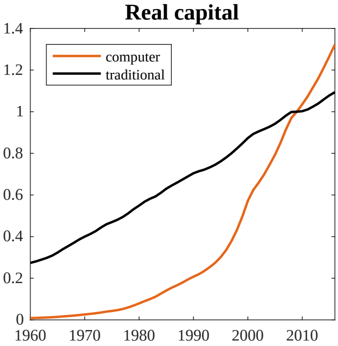
        $\rightarrow$ computer capital deepening
2. differences across sectors
    - sectoral and occupational reallocation of employment closely linked
    - capital intensity?

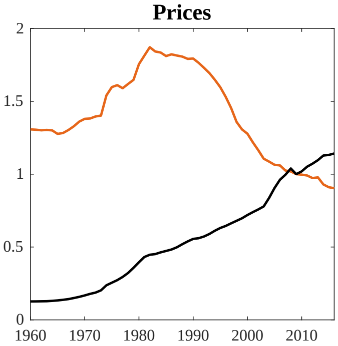
Labor income share by sector 1947-2017



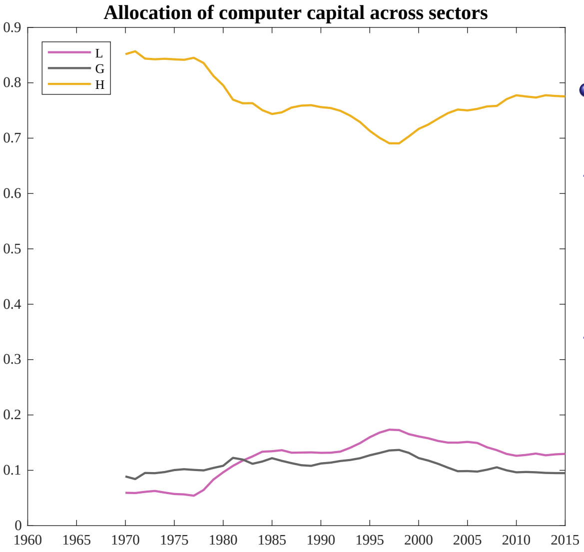
- labor share = compensation of employees / gross VA
- BEA data on components of VA
- combine two:
  - SIC until 1997
  - NAICS from 1998

ICT and non-ICT capital 1960-2015





Computer capital across sectors 1970-2015



- EU Klems data on capital by sector:
  - computer: computing and communications equipment, computer software and databases
  - traditional: everything else

We will use these data to back out sector-specific factor augmenting technologies

1. within sectors: the shares of factor incomes and factor prices
2. across sectors: the relative price across sectors, and the price of factor inputs
3. over time: the growth of GDP per worker

Inferring biased technological change

Sectoral production

⇒ inputs

- three types of occupational labor:
  manual (m), routine (r), abstract (a)
- computer capital (c)
- traditional capital (k)

⇒ functional form: nested CES

- computer capital more substitutable with routine labor
- traditional capital also not Cobb-Douglas: differently changing labor income share by sector

⇒ technological change

- as general as possible: specific to sector & factor input
- allows model to match factor input use and income shares
- do not impose a priori that tech change is specific to sector or occupation

Production

nested CES production function in all sectors, $J \in \{L, G, H\}$

$$Y_J = \left[\left((\alpha_{mJ} l_{mJ})^{\frac{\rho-1}{\rho}} + \left[(\alpha_{rJ} l_{rJ})^{\frac{\sigma_c-1}{\sigma_c}} + (\alpha_{cJ} c_J)^{\frac{\sigma_c-1}{\sigma_c}} \right]^{\frac{\sigma_c}{\sigma_c-1}\frac{\rho-1}{\rho}} \right. \right.$$

$$\left. \left. + (\alpha_{aJ} l_{aJ})^{\frac{\rho-1}{\rho}} \right)^{\frac{\rho}{\rho-1}\frac{\sigma-1}{\sigma}} + (\alpha_{kJ} k_J)^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}}$$

- α_{oJ} sector-occupation specific labor augmenting technology
- α_{cJ}, α_{kJ} sector-type specific capital augmenting technology
- ρ, σ, σ_c common across sectors
- firms operate under perfect competition: take as given
  - the rental rates of ICT and non-ICT capital
  - and the sector-occupation specific wage rates

Optimal input use and relative αs within sectors

$\rightarrow$ firm FOCs on manual and abstract labor give

$$\frac{l_{aJ}}{l_{mJ}} = \left(\frac{w_{mJ}}{w_{aJ}}\right)^{\rho} \left(\frac{\alpha_{aJ}}{\alpha_{mJ}}\right)^{\rho-1}$$

$$\frac{w_{aJ} l_{aJ}}{w_{mJ} l_{mJ}} = \left(\frac{w_{mJ}}{w_{aJ}}\right)^{\rho-1} \left(\frac{\alpha_{aJ}}{\alpha_{mJ}}\right)^{\rho-1}$$

Optimal input use and relative αs within sectors

$\rightarrow$ firm FOCs on manual and abstract labor give

$$\frac{l_{aJ}}{l_{mJ}} = \left(\frac{w_{mJ}}{w_{aJ}}\right)^{\rho} \left(\frac{\alpha_{aJ}}{\alpha_{mJ}}\right)^{\rho-1}$$

$$\frac{\theta_{aJ}}{\theta_{mJ}} = \frac{w_{aJ} l_{aJ}}{w_{mJ} l_{mJ}} = \left(\frac{w_{mJ}}{w_{aJ}}\right)^{\rho-1} \left(\frac{\alpha_{aJ}}{\alpha_{mJ}}\right)^{\rho-1}$$

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$$\frac{\theta_{aJ}}{\theta_{mJ}} = \frac{w_{aJ} l_{aJ}}{w_{mJ} l_{mJ}} = \left(\frac{w_{mJ}}{w_{aJ}}\right)^{\rho-1} \left(\frac{\alpha_{aJ}}{\alpha_{mJ}}\right)^{\rho-1}$$

$$\frac{\alpha_{aJ}}{\alpha_{mJ}} = \frac{w_{aJ}}{w_{mJ}} \left(\frac{\theta_{aJ}}{\theta_{mJ}}\right)^{\frac{1}{\rho-1}}$$

Optimal input use and relative αs within sectors

$\rightarrow$ firm FOCs on manual and abstract labor give

$$\frac{l_{aJ}}{l_{mJ}} = \left(\frac{w_{mJ}}{w_{aJ}}\right)^{\rho} \left(\frac{\alpha_{aJ}}{\alpha_{mJ}}\right)^{\rho-1}$$

$$\frac{\theta_{aJ}}{\theta_{mJ}} = \frac{w_{aJ} l_{aJ}}{w_{mJ} l_{mJ}} = \left(\frac{w_{mJ}}{w_{aJ}}\right)^{\rho-1} \left(\frac{\alpha_{aJ}}{\alpha_{mJ}}\right)^{\rho-1}$$

$$\frac{\alpha_{aJ}}{\alpha_{mJ}} = \frac{w_{aJ}}{w_{mJ}} \left(\frac{\theta_{aJ}}{\theta_{mJ}}\right)^{\frac{1}{\rho-1}}$$

$\rightarrow$ similarly the FOCs on routine labor and computer capital give

$$\frac{\alpha_{cJ}}{\alpha_{rJ}} = \frac{R_c}{w_{rJ}} \left(\frac{\Theta_{cJ}}{(1-\Theta_J)\theta_{rJ}}\right)^{\frac{1}{\sigma_c-1}}$$

$\rightarrow$ express relative αs in terms of observables and elasticities

Optimal input use and relative αs within sectors

$\rightarrow$ given optimal routine labor/computer capital use, the FOCs on routine and manual labor imply

$$\frac{\alpha_{mJ}}{\alpha_{rJ}} = \frac{w_{mJ}}{w_{rJ}} \left[1 + \frac{\Theta_{cJ}}{(1-\Theta_J)\theta_{rJ}}\right]^{\frac{\rho-\sigma_C}{(\sigma_C-1)(\rho-1)}} \left(\frac{\theta_{mJ}}{\theta_{rJ}}\right)^{\frac{1}{\rho-1}}$$

$\rightarrow$ given optimal routine labor/computer capital and optimal manual/abstract labor use, the FOCs on capital and manual labor imply

$$\frac{\alpha_{kJ}}{\alpha_{mJ}} = \frac{R}{w_{mJ}} \left(\frac{1}{\theta_{mJ}}\right)^{\frac{1}{\rho-1}} \left(\frac{\Theta_J - \Theta_{cJ}}{1-\Theta_J}\right)^{\frac{1}{\sigma-1}} \left(1 + \frac{\Theta_{cJ}}{1-\Theta_J}\right)^{\frac{\sigma-\rho}{(\rho-1)(\sigma-1)}}$$

Relative αs across sectors and over time

$\rightarrow$ optimal input use and the FOC on non-ICT capital implies

$$p_J = \frac{R}{\alpha_{kJ}} (\Theta_J - \Theta_{cJ})^{\frac{1}{\sigma-1}}$$

$$\frac{\alpha_{kH}}{\alpha_{kG}} = \frac{p_G}{p_H} \left(\frac{\Theta_H - \Theta_{cH}}{\Theta_G - \Theta_{cG}} \right)^{\frac{1}{\sigma-1}}$$

$\rightarrow$ can calculate Y_J conditional on α_{mH} given l_{mJ} and relative optimal input use

$\Rightarrow$ evolution of α_{mH} over time pinned down by growth in real GDP per worker

Implementation

We need three elasticities

1. elasticity of capital and aggregate labor: $\sigma = 0.8$
   consensus lies between 0.6 and 0.85
2. elasticity of computer capital and routine labor: $\sigma_c = 8$
   consensus is that these are very good substitutes $\sigma_c \gg 1.5$
3. elasticity between different occupations: $\rho = 0.7$
   values used in the literature between 0.5 and 0.9

We need from the data

- labor income shares of occupations within each sector details
  sector-occupation wages details
- capital & computer capital income share for each sector,
  both rental rates details
- relative sectoral prices
- sector-occ emp shares, growth rate of real GDP per worker

Growth rates of factor-augmenting technologies

Annualized change in α between 1960 and 2010

	occupations			capital	
	manual	routine	abstract	non-ICT	ICT
L	0.9894	1.0319	0.9931	1.0096	1.0420
G	0.9299	1.0682	1.0152	0.9762	1.0759
H	0.9869	1.0120	0.9750	1.0224	1.0120

$\rightarrow$ amongst all production factors, routine labor and ICT capital have the highest growth in all sectors

$\rightarrow$ differences across sectors in tech progress of a given factor

$\rightarrow$ higher measured labor productivity growth in G masks differential tech progress of factors

The role of changing input use and technologies

Quantifying the role

1. of changing input use
    - use extracted αs
    - fix inputs at initial level
2. of changing technologies
    - use actual inputs
    - fix αs at initial level

Role of changing *capital* inputs

sectoral lab. prod. growth using **extracted αs** and

FIXED INPUTS	growth rate L	G	H	diff in growth rate $G-L$	$G-H$
data	1.0166	1.0274	1.0090	0.0108	0.0184
all	1.0127	1.0117	1.0041	-0.0010	0.0076

$\rightarrow$ changing input use important both for level of growth and sectoral differences

Role of changing *capital* inputs

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all	1.0127	1.0117	1.0041	-0.0010	0.0076
capital	1.0117	1.0226	1.0008	0.0109	0.0218

$\rightarrow$ changing input use important both for level of growth and sectoral differences

$\rightarrow$ (differential) capital deepening important for level

Role of changing *capital* inputs

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FIXED INPUTS	growth rate L	growth rate G	growth rate H	diff in growth rate $G-L$	diff in growth rate $G-H$
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all	1.0127	1.0117	1.0041	-0.0010	0.0076
capital	1.0117	1.0226	1.0008	0.0109	0.0218
non-ICT cap	1.0122	1.0230	1.0020	0.0108	0.0210
ICT cap	1.0161	1.0270	1.0077	0.0109	0.0193

$\rightarrow$ changing input use important both for level of growth and sectoral differences

$\rightarrow$ (differential) capital deepening important for level

$\rightarrow$ especially non-ICT capital deepening

$\rightarrow$ ICT capital deepening not that important

Role of changing *labor* inputs

sectoral lab. prod. growth using **extracted** α**s** and

FIXED INPUTS	growth rate			diff in growth rate	
	L	G	H	G-L	G-H
data	1.0166	1.0274	1.0090	0.0108	0.0184
all	1.0127	1.0117	1.0041	-0.0010	0.0076
labor	1.0174	1.0165	1.0116	-0.0009	0.0049

$\rightarrow$ changing labor use important for level of growth (in G) and sectoral differences

Role of changing *labor* inputs

sectoral lab. prod. growth using **extracted** α**s** and

FIXED INPUTS	growth rate L	growth rate G	growth rate H	diff in growth rate G-L	diff in growth rate G-H
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all	1.0127	1.0117	1.0041	-0.0010	0.0076
labor	1.0174	1.0165	1.0116	-0.0009	0.0049
occ shares within sec	1.0158	1.0248	1.0074	0.0090	0.0174

$\rightarrow$ changing labor use important for level of growth (in G) and sectoral differences

$\rightarrow$ occupational employment share changes within sectors have a rather small effect

Role of changing *labor* inputs

sectoral lab. prod. growth using **extracted** α**s** and

FIXED INPUTS	growth rate			diff in growth rate	
	L	G	H	G-L	G-H
data	1.0166	1.0274	1.0090	0.0108	0.0184
all	1.0127	1.0117	1.0041	-0.0010	0.0076
labor	1.0174	1.0165	1.0116	-0.0009	0.0049
occ shares within sec	1.0158	1.0248	1.0074	0.0090	0.0174
sec emp	1.0183	1.0188	1.0134	0.0005	0.0054

$\rightarrow$ changing labor use important for level of growth (in G) and sectoral differences

$\rightarrow$ occupational employment share changes within sectors have a rather small effect

$\rightarrow$ sectoral employment share changes are important

Role of changing technologies

sectoral lab. prod. growth using **actual factor inputs** and

FIXED TECHNOLOGIES	growth rate			diff in growth rate	
	L	G	H	$G-L$	$G-H$
data	1.0166	1.0274	1.0090	0.0108	0.0184
all	1.0024	1.0077	1.0044	0.0053	0.0033

$\rightarrow$ tech. progress key for level of and for differences in growth rates

Role of changing technologies

sectoral lab. prod. growth using **actual factor inputs** and

FIXED TECHNOLOGIES	growth rate L	growth rate G	growth rate H	diff in growth rate $G - L$	diff in growth rate $G - H$
data	1.0166	1.0274	1.0090	0.0108	0.0184
all	1.0024	1.0077	1.0044	0.0053	0.0033
capital	1.0120	1.0391	0.9988	0.0271	0.0403

→ tech. progress key for level of and for differences in growth rates

→ capital-augmenting tech. change increases L & H prod. growth, and depresses G

Role of changing technologies

sectoral lab. prod. growth using **actual factor inputs** and

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data	1.0166	1.0274	1.0090	0.0108	0.0184
all	1.0024	1.0077	1.0044	0.0053	0.0033
capital	1.0120	1.0391	0.9988	0.0271	0.0403
ICT capital	1.0162	1.0270	1.0085	0.0108	0.0185
non-ICT capital	1.0124	1.0396	0.9992	0.0272	0.0404

→ tech. progress key for level of and for differences in growth rates

→ capital-augmenting tech. change increases L & H prod. growth, and depresses G – driven by non-ICT capital

Role of changing technologies

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ICT capital	1.0162	1.0270	1.0085	0.0108	0.0185
non-ICT capital	1.0124	1.0396	0.9992	0.0272	0.0404
labor	1.0083	1.0084	1.0160	0.0001	-0.0076

→ tech. progress key for level of and for differences in growth rates

→ capital-augmenting tech. change increases L & H prod. growth, and depresses G – driven by non-ICT capital

→ labor-augmenting technological change is key

Recap of results so far

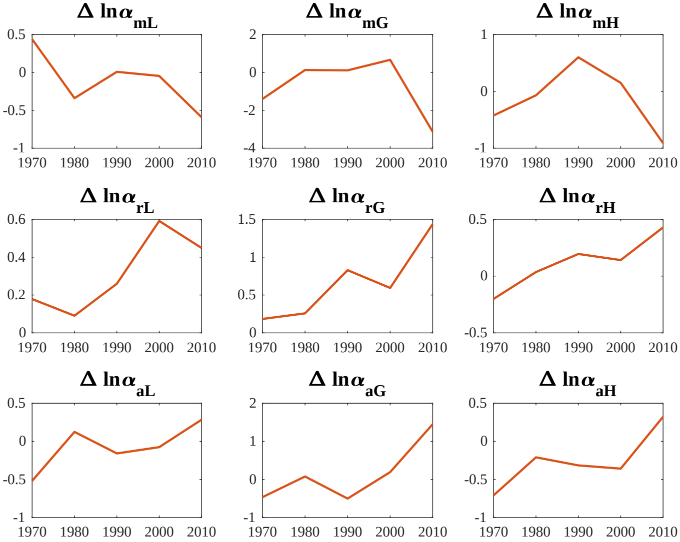
- changing input use important for both level of and differences in sectoral growth rates
  - capital (especially non-ICT) important for level
  - changing labor use, especially cross-sector allocation important for differences
- factor-augmenting technological change important for level and differences
  - capital-augmenting tech. change increases L & H prod. growth and depresses G
  - labor-augmenting tech. change key

$\Rightarrow$ closer inspection of labor-augmenting tech. change

are there components common to occupations/sectors?

Decomposing labor-augmenting tech. change

Labor augmenting technological change



Factor model decomposition

Relate cell technology change to a neutral, a sector, an occupation effect, as well as a residual

$$\begin{aligned}\Delta \ln \alpha_{oJ,t} \equiv & \ln \alpha_{oJ,t} - \ln \alpha_{oJ,t-1} \\ = & \beta_t + \gamma_{J,t} + \delta_{o,t} + \varepsilon_{oJ,t}\end{aligned}$$

where

- β_t – changes common to all cells
- $\gamma_{J,t}$ – changes common within a sector
- $\delta_{o,t}$ – changes common within an occupation
- $\varepsilon_{oJ,t}$ – changes idiosyncratic to a cell

use weights $\omega_{oJ,t} = \frac{VA_{J,t}(1-\Theta_{J,t})\theta_{oJ,t} + VA_{J,t-1}(1-\Theta_{J,t-1})\theta_{oJ,t-1}}{2}$ to reflect relative importance of cells

Factor model decomposition

$$\Delta \ln \alpha_{oJ,t} = \beta_t + \gamma_{J,t} + \delta_{o,t} + \varepsilon_{oJ,t}$$

- restrict average sector effect to be zero
  $\sum_o \sum_J \omega_{oJ,t}\gamma_{J,t} = 0$ for every t
- restrict average occupation effect to be zero
  $\sum_J \sum_o \omega_{oJ,t}\delta_{o,t} = 0$ for every t

$\Rightarrow$ β_t captures average labor augmenting technological change

Changes due to Sector and Occupation Factors

- 'Full factor' technology: $\widehat{\Delta \ln \alpha}_{oJ,t} = \widehat{\beta}_t + \widehat{\gamma_{J,t}} + \widehat{\delta_{o,t}}$

- 'Sector-only' technology: $\widehat{\Delta \ln \alpha}^{sec}_{oJ,t} = \widehat{\beta}_t + \widehat{\gamma_{J,t}}$

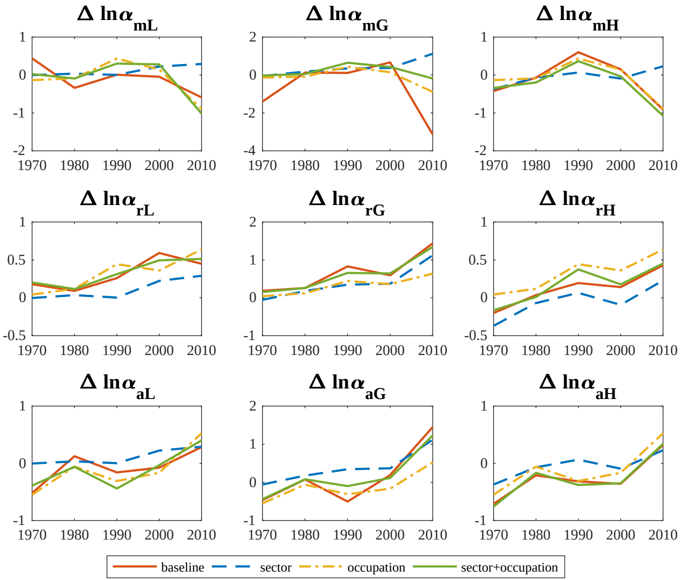
  $\rightarrow$ shut down differences coming from the occ components

- 'Occupation-only' technology: $\widehat{\Delta \ln \alpha}^{occ}_{oJ,t} = \widehat{\beta}_t + \widehat{\delta_{o,t}}$

  $\rightarrow$ shut down differences coming from the sec components

- 'Neutral' technology: $\widehat{\Delta \ln \alpha}^{neut}_{oJ,t} = \widehat{\beta}_t$

Predictions based on common components



Measuring the importance of occupation and sector components

Distance measure between baseline and predicted $\Delta \ln \alpha_{oJ}$

$$Dist = \frac{\sum_{o,J,t} \omega_{oJ,t} (\widehat{\Delta \ln \alpha}_{oJ,t} - \Delta \ln \alpha_{oJ,t})^2}{\sum_{o,J,t} \omega_{oJ,t} (\Delta \ln \alpha_{oJ,t} - \overline{\Delta \ln \alpha})^2} \geq 0$$

Related to R^2, in certain cases $R^2 = 1 - Dist$

$$R^2 = \frac{\sum_{o,J,t} \omega_{oJ,t} (\widehat{\Delta \ln \alpha}_{oJ,t} - \overline{\Delta \ln \alpha})^2}{\sum_{o,J,t} \omega_{oJ,t} (\Delta \ln \alpha_{oJ,t} - \overline{\Delta \ln \alpha})^2}$$

Contribution of Sector and Occupation Factors

Distance measures for a range of elasticities: $\rho \in (0.5, 0.9)$

ρ	**neutral**	**full factor**	**sector**	**occupation**
0.5	0.814	0.068	0.282	0.431
0.6	0.842	0.095	0.395	0.380
0.7	**0.882**	**0.134**	**0.556**	**0.320**
0.8	0.933	0.184	0.765	0.266
0.9	0.981	0.233	0.968	0.250

$\rightarrow$ labor-augmenting technology is not neutral

$\rightarrow$ sector & occupation components jointly explain the evolution of productivities well

$\rightarrow$ occupation component drives a large fraction of this, esp. for higher elasticities

$\rightarrow$ sector component also plays a role

Role of occupation and sector components

sectoral lab. prod. growth using **actual inputs** and

counterfactual technologies	growth rate L	growth rate G	growth rate H	diff in growth rate G-L	diff in growth rate G-H
data	1.0166	1.0274	1.0090	0.0108	0.0184
neutral	1.0113	1.0101	1.0186	-0.0012	-0.0085
full factor	1.0165	1.0280	1.0083	0.0115	0.0197
sector	1.0141	1.0235	1.0136	0.0094	0.0099
occupation	1.0161	1.0144	1.0167	-0.0017	-0.0023

$\rightarrow$ bias in tech. change across cells important

$\rightarrow$ joint sector & occupation prod. changes replicate data well

$\rightarrow$ neither sec nor occ component alone is enough $\rightarrow$ points to interaction between sector and occ component

- note: occupation component is not driving sectoral differences

Summary

- nested CES production function in each sector
    - with sector-factor specific productivities
    - to allow matching rich pattern of factor income shares across sectors
    - use data to extract productivity paths
- analyze role of factor inputs and technologies in measured sectoral labor productivity

    - changing input use important

    $\rightarrow$ capital deepening for level of growth

    $\rightarrow$ sectoral labor use for differences

    - technological change is key

    $\rightarrow$ especially labor-augmenting tech. change

Summary

Examine labor-augmenting technological change

- factor model to decompose sector-occupation specific labor-augmenting tech. change
  - sec & occ components jointly explain tech. changes well
  - largest role of tech. change that is biased across occupations
  - relatively small role for technology biased across sectors
- however, for measured sectoral lab. productivity growth both components are crucial

Thank you

Industry classification

1. Low-skilled services: personal services, entertainment, transport, low-skilled business and repair services (automotive rental and leasing, automobile parking and carwashes, automotive repair and related services, electrical repair shops, miscellaneous repair services), retail trade, wholesale trade
2. Goods: agriculture, forestry and fishing, mining, construction, manufacturing
3. High-skilled services: professional and related services, finance, insurance and real estate, communications, high-skilled business services, communications, utilities, public administration

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Occupation classification

1. Manual: low-skilled non-routine
   housekeeping, cleaning, protective service, food prep and service, building, grounds cleaning, maintenance, personal appearance, recreation and hospitality, child care workers, personal care, service, healthcare support
2. Routine
   farmers, construction trades, extractive, machine operators, assemblers, inspectors, mechanics and repairers, precision production, transportation and material moving occupations, sales, administrative support
3. Abstract: skilled non-routine
   managers, management related, professional specialty, technicians and related support

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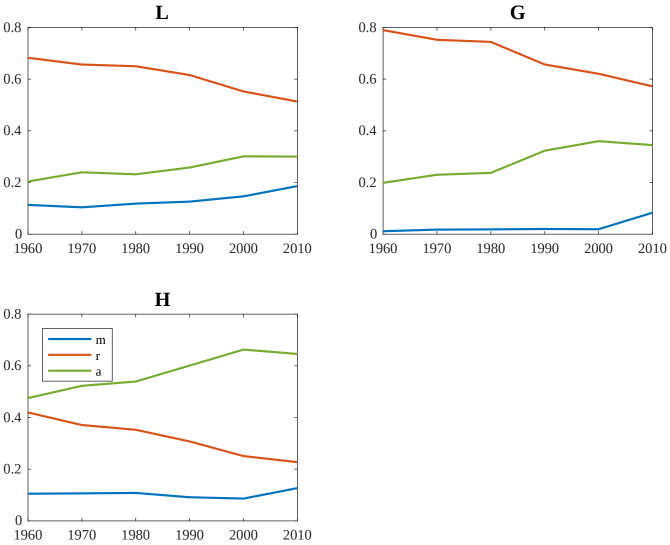
Occupational income shares 1960-2010



Source: Authors' own calculations from US Census, ACS & BEA data ▸ back

Sector-occupation wage rates

- wages pinned down by accounting identity:
  - income received by occupation o workers in sector J can be written in two ways
    - $Y \cdot VA_J(1-\Theta_J)\theta_{oJ}$
    - $w_{oJ} l_{oJ}$
  - normalize all prices and wages by nominal GDP

$$w_{oJ} = \frac{VA_J(1-\Theta_J)\theta_{oJ}}{l_{oJ}}$$

- difference from the one implied by the Census: non-wage compensation included in labor income share

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Efficiency labor

→ implicit assumption: each hour worked in a sec-occ cell is the same
→ alternative: Mincer wage regression

$$\log w_{ioJt} = \delta_{oJt} + \beta' X_{it} + \varepsilon_{ioJt}$$

- two options:
  - construct sec-occ cell efficiency units per hour $\widehat{e}_{ioJt}$
  - construct sec-occ cell unit wages $\widehat{w}_{oJt}$ → back out

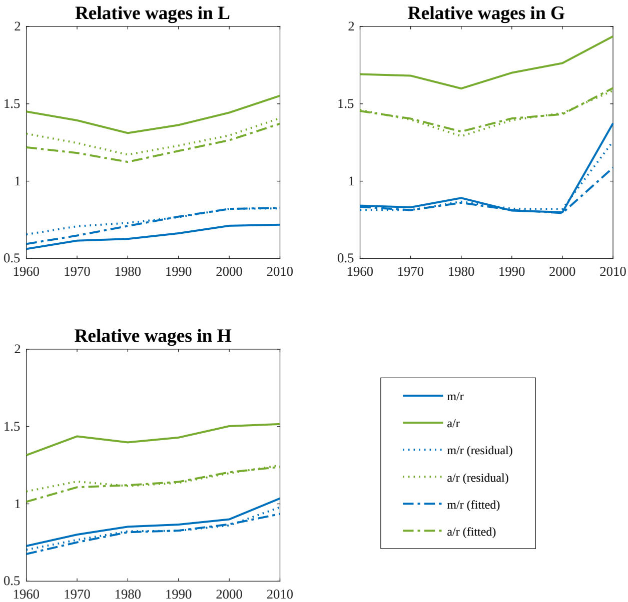
$$\widetilde{e}_{ioJt} = \frac{\text{labor income of } i \text{ (in } o, J, t)}{l_{ioJt}\widehat{w}_{oJt}}$$

- take average by cell-year and back out

$$w_{oJt} = \frac{VA_{Jt}(1 - \Theta_{Jt})\theta_{oJt}}{l_{oJt}\overline{e}_{oJt}}$$

- in both cases the firm chooses $n_{oJ} \equiv e_{oJ} l_{oJ}$ in each period

Implied relative wages within sectors



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Additional data

from BEA get for ICT and non-ICT capital:

- price index: p_c and p_k
- depreciation rate: δ_c and δ_k

infer

- rental rates from
  - no arbitrage between the two types of capital

$$\frac{R_c + (1-\delta_c)p_c'}{p_c} = \frac{R + (1-\delta_k)p_k'}{p_k}$$

  - accounting identity

$$Rk + R_c c = \sum_J VA_J \Theta_J$$

- income share of ICT capital by sector from

$$VA_J \Theta_{cJ} = R_c \widetilde{c}_J c$$

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