

# Technology-Skill Complementarity and Labor Displacement: Evidence from Linking Two Centuries of Patents with Occupations

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## Facts:

- Worker earnings have grown slower than labor productivity
  - ▶ Labor share of output has declined
- Skill premium has increased along with income inequality

**Question:** To what extent did technological change contribute to these worker outcomes?

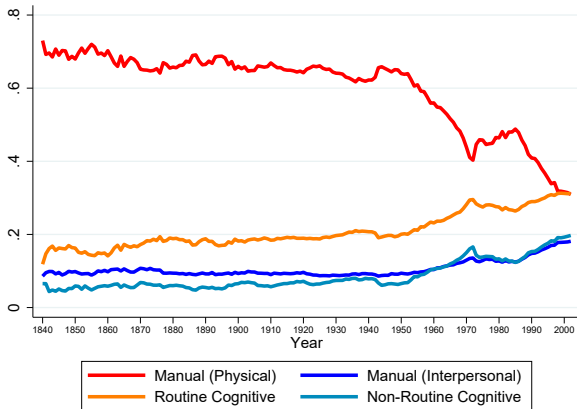
- Impact of technological change on workers hard to measure directly except in specific examples.

**This paper:** Construct direct measures of workers' technological exposure using data and occupation task descriptions.

# What we do

- Leverage state-of-the-art techniques in textual analysis to identify breakthrough technologies affecting specific worker groups (occupations).
  - ▶ Identify significant innovations through patent textual networks.
  - ▶ Relate these innovations to **specific workers** based on DOT/ONET occupation task descriptions.
- Construct time-series indices of occupation-specific technical change that span the last two centuries.
  - ▶ Examine the response of employment and wages to technology shocks both at the aggregate as well as the individual level.
  - ▶ Interpret our empirical findings through the lens of a model of technology-skill complementarity with displacement.

## Preview: Exposure to Technological Change Over Time, Occupation Task Categories



### Examples:

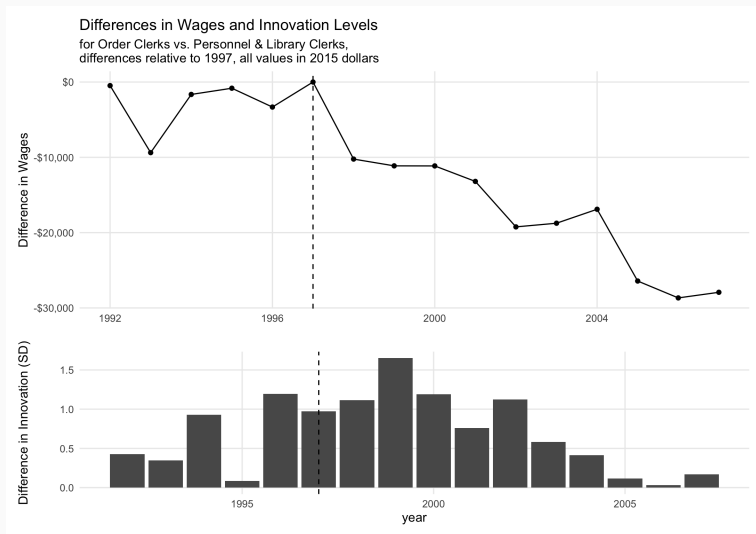
**Manual (physical):** vehicle/machine operators, electricians, mechanics

**Routine cognitive:** technicians, clerks, programmers

**Manual (interpersonal):** teachers, counselors, psychologists

**Non-routine cognitive:** surgeons, managers, engineers

# Order Clerks versus Personnel and Library Clerks



# Findings

1. At the industry level, improvements in technology lead to
  - ▶ higher labor productivity
  - ▶ decline in the labor share
2. At the occupation and worker level, technological change is **consistently negatively** related to employment and wage growth
  - ▶ Middle-skill occupations more exposed
  - ▶ Negative relation with employment growth consistent over last 150 years
3. Effects are heterogenous (though consistently negative) across groups; magnitudes larger for:
  - ▶ non-college educated workers
  - ▶ older workers
  - ▶ more highly-paid workers

# Implications

- High-income workers experience the largest declines in labor earnings.
  - ▶ Hard to reconcile with standard view of technology-skill complementarity (skill-biased change, see e.g. Krusell et al, 2000)
- We modify the standard model to allow for skill displacement
  - ▶ Technology is still more complementary to high-skill labor inputs
  - ▶ However, as technology improves, some workers lose skills
  - ▶ Displacement introduces a wedge between changes in the skill premium and the wage growth of (currently-skilled) workers.
  - ▶ Higher labor income risk for (incumbent) skilled workers
- Calibrated model fits our facts in the presence of technology-skill complementarity

# Measurement

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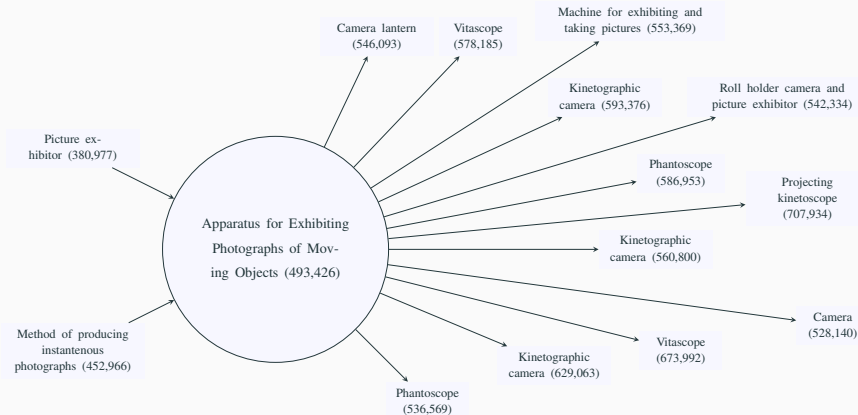
# Innovation is hard to measure directly

- Our starting goal is patents. Why?
  - ▶ By definition, patents relate to new inventions  
(though not all valuable inventions are patentable)
  - ▶ They measure output not inputs  
(important if you think research productivity is slowing down)
- Two major challenges:
  1. Not all patents are equally valuable inventions.
    - pro-patent shift in US policy (Hall and Zeidonis 2001)
    - we need to weigh important patents differently from ones that are trivial.
  2. How to identify workers' exposure to different technologies?

# Measurement: Broad Idea

1. We follow Kelly, Papanikoloau, Seru, and Taddy (2021) (hereafter KPST) and identify important patents as those that:
  - ▶ are distinct from previous patents but are related to subsequent patents (i.e., **they are novel and impactful**)
  - ▶ **Implementation:** We need to measure the similarity between a given patent and prior and subsequent patents (within a window).
2. We identify the exposure of occupation  $j$  to technology as
  - ▶ # of important patents that are related to the tasks occupation  $j$  performs
  - ▶ **Implementation:** We need to measure the similarity between a given patent and occupation task descriptions (ONET/DOT)

# Patent-patent similarity example: Moving Pictures



# Measuring technical change

- KPST identify important patents as those that are both
  - ▶ novel (fewer past connections)      and
  - ▶ impactful (have more future connections).
- Measure Technological Change in an Industry:
  - ▶ Count the # of patents / year at the right tail of the distribution of importance (breakthroughs)
  - ▶ Map these to industry NAICS codes using patent tech class crosswalks from **Goldschlag et al 2016**
- Relate to industry outcomes

$$\log(Y_{j,t+k}) - \log(Y_{j,t}) = \alpha(k) + \beta(k)\psi_{j,t} + \delta(k)Z_{j,t} + \varepsilon_{j,t}, \quad k = 1 \dots 6$$

Furniture, Textiles, Apparel

Transportation Equipment

Machinery Manufacturing

Metal Manufacturing

Wood, Paper, Printing

Construction

Plastics, Rubber

Mineral Processing

Utilities

Mining, Extraction

Electrical Equipment

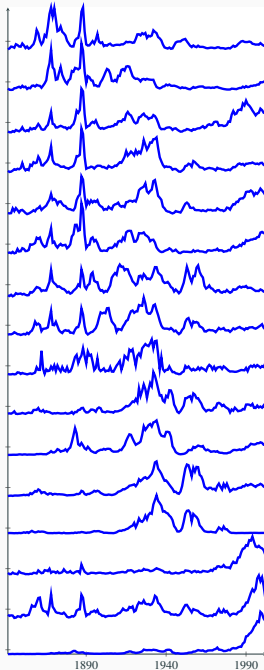
Chemical Manufacturing

Petroleum, Coal

Medical Equipment

Agriculture, Food

Computers, Electronics



1860

1880

1900

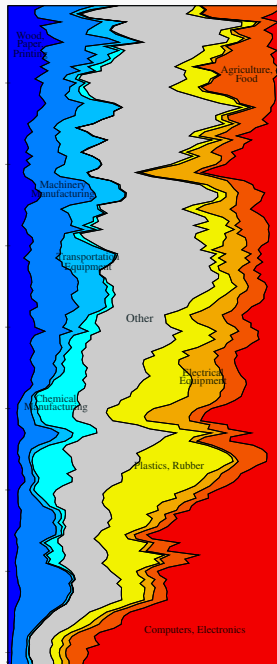
1920

1940

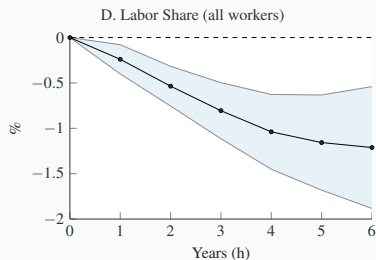
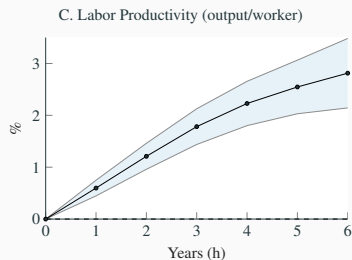
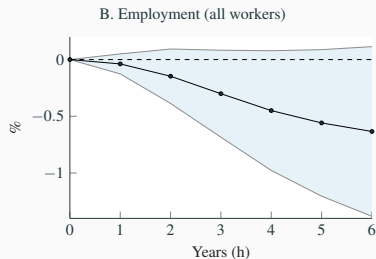
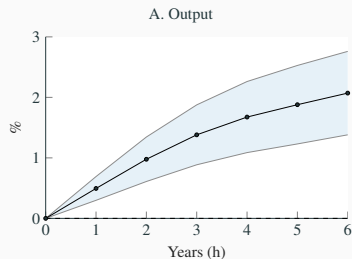
1960

1980

2000



# Innovation: Productivity vs Labor Share



Sample: Manufacturing, 1958–2018

# Summary and Next Steps

- At the industry level, technological change followed by:
  - ▶ higher output and labor productivity
  - ▶ weak decline in industry employment
  - ▶ a decline in labor share
- Is technological change labor-saving on average? Answer this question by exploiting cross-worker differences
  - ▶ ATMs likely displaced bank tellers; impact on stock brokers unclear.
- To dig deeper into these facts, we next construct measures of technological change at the **occupation** level.

# Measuring workers' technology exposure

- **Methodology:** connect specific technologies (patents) to specific workers (occupations) based on the textual similarity between the description of the innovation and the workers' task description.
- **Our prior:** Since our approach is based on measuring task overlap, primarily identifies patents that **substitute rather than complement worker tasks**.
  - ▶ We later verify this is the case by comparing our approach to a statistical factor constructed to maximize predictability of negative worker outcomes in sample.



# Occupation Task description, example

## Summary Report for: 19-3011.00 - Economists

Updated 2019  
Bright Outlook

Conduct research, prepare reports, or formulate plans to address economic problems related to the production and distribution of goods and services or monetary and fiscal policy. May collect and process economic and statistical data using sampling techniques and econometric methods.

**Sample of reported job titles:** Economic Analyst, Economic Consultant, Economic Development Specialist, Economist, Forensic Economist, Project Economist, Research Analyst, Research Associate, Revenue Research Analyst, Tax Economist

Also see: [Environmental Economists](#)

View report:

**Summary**

[Details](#)

[Custom](#)

[Tasks](#) | [Technology Skills](#) | [Tools Used](#) | [Knowledge](#) | [Skills](#) | [Abilities](#) | [Work Activities](#) | [Detailed Work Activities](#) | [Work Context](#) | [Job Zone](#) | [Education](#) | [Credentials](#) | [Interests](#) | [Work Styles](#) | [Work Values](#) | [Related Occupations](#) | [Wages & Employment](#) | [Job Openings](#) | [Additional Information](#)

### Tasks

+ - All 11 displayed

- + Study economic and statistical data in area of specialization, such as finance, labor, or agriculture.
- + Conduct research on economic issues and disseminate research findings through technical reports or scientific articles in journals.
- + Compile, analyze, and report data to explain economic phenomena and forecast market trends, applying mathematical models and statistical techniques.
- + Supervise research projects and students' study projects.
- + Teach theories, principles, and methods of economics.
- + Study the socioeconomic impacts of new public policies, such as proposed legislation, taxes, services, and regulations.
- + Formulate recommendations, policies, or plans to solve economic problems or to interpret markets.
- + Explain economic impact of policies to the public.
- + Provide advice and consultation on economic relationships to businesses, public and private agencies, and other employers.
- + Forecast production and consumption of renewable resources and supply, consumption, and depletion of non-renewable resources.
- + Develop economic guidelines and standards and prepare points of view used in forecasting trends and formulating economic policy.

# Measuring Patent Similarity

## Goal: measure distance between invention on worker tasks

### Patent



### Task Description

5,911,135

#### SYSTEM FOR MANAGING FINANCIAL ACCOUNTS BY A PRIORITY ALLOCATION OF FUNDS AMONG ACCOUNTS CROSS REFERENCE TO RELATED APPLICATIONS

This application is a continuation of U.S. patent application Ser. No. 07/406,377, filed Sep. 15, 1989 now abandoned, which is a continuation of U.S. patent application Ser. No. 07/038,817, filed Apr. 15, 1987 now U.S. Pat. No. 4,951,685.

#### BACKGROUND OF THE INVENTION

This relates to a method and apparatus which provides an integrated financial product package. This system is realized, in the preferred embodiment, when implemented in a real-time computer system, and accordingly will be described in such context. It will be understood, however, that the invention may be applied to numerous other contexts.

Secured lending against homes has been practiced for many years, and recently a host of new financial products have been introduced in an effort to make mortgage lending more attractive to financial institutions and to make housing more affordable to prospective homeowners. Despite the proliferation of new mortgage products in this intensely crowded and competitive area, prior practices have not been entirely successful in meeting the goals of both the mortgagee and the financial institutions. Moreover, product proliferation in the market for financial services has produced the consumer with a confusing array of choices without a convenient or mathematically correct means of selecting the best combination of financial services to realize the consumer's financial objectives.

Financial institutions have traditionally lent funds to individuals on a fully secured basis, with an interest rate greater than their own cost of funding the loan. In the last few years however, the financial industry has been challenged and now it is possible for a variety of financial institutions and firms that market financial services (hereinafter referred to as "financial institutions") to sell an entire range of financial products. Thus, in addition to the traditional objectives of a mortgage, many financial institutions now offer mortgage lending as a vehicle to encourage the borrower to purchase one or more financial services products. Many new mortgage lenders, to facilitate the purchase of such services.

From the point of view of the mortgage, problems will result with the relative inflexibility of the mortgage. The mortgagee is locked in to a payment schedule which typically extends over most of the years in which he is working.

The recently enacted Tax Reform Act of 1986 (T.R.A.) has also affected the situation. While it eliminated many tax deductions and tax shelters, it provided for the continued deductibility of interest payments on mortgages up to the full amount of the cost of two homes and any improvements thereon. Moreover, certain insurance products, annuities, and pension plans continue to be attractive "tax-favored" investments under the new law.

Present mortgage practices, however, do not take advantage of deregulation of the financial services industry and the new tax laws and are not configured to offer the mortgagee a full range of financial services that would help him to maximize his financial return.

#### SUMMARY OF THE INVENTION

The present invention is a method and apparatus for effecting an improved personal financial management pro-

gram incorporating means of implementing, coordinating, supervising, analyzing and reporting upon investments in an array of assets and credit facilities. Through a mathematical programming function the client specifies his financial objectives, a forecast of economic and financial variables, risk preference and the budgetary constraints to which he is subject. The mathematical programming function suggests investments and credit facilities to the client to best realize his financial objectives. Thus, the present invention provides clients a convenient, cost effective, and mathematically rigorous means of maximizing his or her financial well-being. The mathematical programming function presents the financial institution in easily definable means of managing client accounts that have potentially an infinite number of investment opportunities in a way that minimizes the detrimental aspects of enforcing compliance while satisfying the financial institution's objective.

In the preferred embodiment, the central structural element of the integrated financial product package is a type of mortgage that features a variable amortization schedule and is secured by the pledge of real property and one or more other assets. This mortgage is called a Home Owner's Preferred Equity (HOPE) mortgage. Unlike conventional mortgages which provide for regular amortization payments, the mortgage need not be amortized.

Further, the system of the present invention gives the mortgagee the opportunity to maximize his investment earnings by a variety of means including distributing the monies that would normally be used to amortize the mortgage among assets that give him the greatest return. For example, the mortgage, hereinafter referred to as the "client", has the option to use the funds that would otherwise have been used to amortize the mortgage to make a contribution to a pension or retirement account such as an IRA, 401(K), S.E.P. or corporate pension plan. Alternatively, the client may purchase "tax favored" investments such as life insurance or securities in which savings on premium payments or "taxable trading", are not taxed until they are withdrawn.

From the financial institution's perspective, the mortgage used in the system of the present invention is superior to the other forms of mortgages in that (1) it offers the lender an additional source of liquid collateral that will, if properly assessed, continually appreciate in value; (2) the mortgage establishes an asset that will add to the net worth of other financial service products that will produce additional revenue for the financial institution; and (3) the mortgage should quickly gain wide acceptance in the secondary market as the form of mortgage-backed securities or Real Estate Mortgage Investment Credit (REMIC) term income of the mortgage's solid security and longer average life.

At the same time, originating, servicing and selling of other financial service products to the client involves many considerations that a conventional mortgage, for the system to operate properly, the home owner's total monies are adjusted to provide the financial institution with a measure of security for its lending, must always be greater than some imposed minimum standard. Calculation of adjusted total monies requires the financial institution to determine the current value of each asset and multiply it by its current loan to value ratio to arrive at a value that is calculated and checked frequently to reflect a change in the value or quantity of any asset or liability which is part of the system. Thus, for example, if borrowing is made against the cash value of the client's insurance policy or if the value of the client's bond portfolio changes, the asset values must be re-calculated, a new borrowing power must be determined and the new borrowing power must be compared to the

#### Summary Report for: 11-3031.00 - Financial Managers

Plan, direct, or coordinate accounting, investing, banking, insurance, securities, and other financial activities of a branch, office, or department of a financial institution.  
**Sample of reported job titles:** Banking Center Manager (BCM), Branch Manager, Credit Administration Manager, Financial Center Manager, Reg. Service Center Manager

Also see: [Treasurers and Controllers, Investment Fund Managers](#)

View report:	Summary	Details	Custom	Easy Read	Veterans	Español
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[Tasks](#) | [Technology Skills](#) | [Tools Used](#) | [Knowledge](#) | [Skills](#) | [Abilities](#) | [Work Activities](#) | [Detailed Work Activities](#) | [Work Context](#) | [Job Zone](#) | [Credentials](#) | [Interests](#) | [Work Styles](#) | [Related Occupations](#) | [Shades & Environment](#) | [Job Descriptions](#) | [Additional Information](#)

#### Tasks

21 displayed

- Establish and maintain relationships with individual or business customers or provide assistance with problems these customers may encounter.
- Plan, direct, or coordinate the activities of workers in branches, offices, or departments of establishments, such as branch banks, brokerage insurance departments, or credit departments.
- Recruit staff members.
- Prepare operational or risk reports for management analysis.
- Evaluate data pertaining to costs to plan budgets.
- Oversee training programs.
- Examine, evaluate, or process loan applications.
- Approve, reject, or coordinate the approval or rejection of lines of credit or commercial, real estate, or personal loans.
- Oversee the flow of cash or financial instruments.
- Prepare financial or regulatory reports required by laws, regulations, or boards of directors.
- Develop or analyze information to assess the current or future financial status of firms.
- Communicate with stockholders or other investors to provide information or to raise capital.
- Evaluate financial reporting systems, accounting or collection procedures, or investment activities and make recommendations for changes in operating systems, budgets, or other financial control functions.
- Analyze and classify risks and investments to determine their potential impacts on companies.
- Network within communities to find and attract new business.
- Review collection reports to determine the status of collections and the amounts of outstanding balances.
- Establish procedures for custody or control of assets, records, loan collateral, or securities to ensure safekeeping.
- Plan, direct, and coordinate risk and insurance programs of establishments to control risks and losses.
- Review reports of securities transactions or price lists to analyze market conditions.
- Direct insurance negotiations, select insurance brokers or carriers, and place insurance.
- Submit delinquent accounts to attorneys or outside agencies for collection.

# Text Analysis Basics: Representing Text as Data

**Typical Approach:** Represent documents as sparse word vectors

- For two documents  $i$  and  $j$ , construct  $V_i$  and  $V_j$  as a (sparse) word vector of length  $W$  (i.e. the size of the set union for terms in  $(i,j)$ )
  - ▶ Example:  $D1 = \{\text{dog, eat, food}\}$  and  $D2 = \{\text{cat, eat, food}\}$  leads to  $V_1 = [1, 0, 1, 1]$  and  $V_2 = [0, 1, 1, 1]$
- This ‘bag of words’ approach works well when the two documents are written in the same ‘language’ (lots of grammatical overlap)
- Measure similarity across documents based on cosine similarity between  $V_1$  and  $V_2$ .

# Text Analysis Basics: Representing Text as Data

However, the previous approach does not deal with synonyms.

- For example, if  $D1 = \{\text{dog, cat}\}$  and  $D2 = \{\text{puppy, kitten}\}$  then  $V_1 = \{1, 1, 0, 0\}$   $V_2 = \{0, 0, 1, 1\}$  and

$$\text{Cosine Similarity}(V_1, V_2) = \frac{V_1 \cdot V_2}{||V_1|| \times ||V_2||} = 0$$

Even though the two documents have similar meanings.

- This creates a bias towards low similarity if the two documents use different vocabulary
  - ▶ e.g. patent documents vs occupation task descriptions

# Dealing With Synonyms

**Our solution:** use word embeddings (e.g. word2vec).

- Each word  $x_k$  is represented as a 300-dimensional vector (arbitrary basis).
- The (cosine) distance between two word vectors is related to the probability they are synonyms (i.e., they are used in the same context within a set of documents).
- We use word vectors provided by Pennington et al. (2014) that were trained on 42 billion word tokens of web data from Common Crawl.

# Dealing With Synonyms

Represent documents as weighted averages of word vectors:

$$V_i = \sum_{x_k \in A_i} w_{i,k} x_k$$

- Now,  $V_i$  is no longer sparse but has lower dimensionality than before.
- Here  $w_{i,k}$  is the term-frequency-inverse-document-frequency (TFIDF) defined as

$$w_{i,k} \equiv TF_{i,k} \times IDF_k = \frac{f_{k,i}}{\sum_{k' \in \text{doc } i} f_{i,k'}} \times \log \left( \frac{\# \text{ of documents}}{\# \text{ of documents that include term } k} \right)$$

- ▶ IDF is computed separately for patents and job descriptions
- In the example  $D1 = \{\text{dog, cat}\}$  and  $D2 = \{\text{puppy, kitten}\}$ , now Cosine  $\text{Sim}(V_1, V_2) \approx 0.81$ .

# From Text to Vector Representation

Example:

Document  $i$ : “The quick brown fox jumped over the lazy dog.”

→ Get nouns and verbs (lemmatized) :  $\{fox, jump, dog\}$

→ Vector representation of phrase:

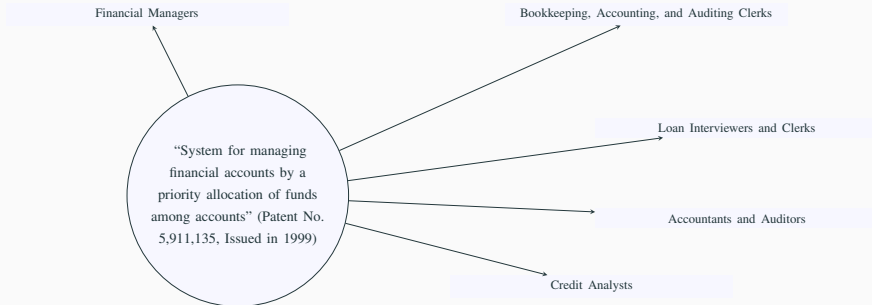
$$V_i = w_{i,fox}x_{fox} + w_{i,jump}x_{jump} + w_{i,dog}x_{dog}$$

$w_{i,k}$  is the TF-IDF weight as explained before

$x_k$  is a 300-dimensional vector whose location in space is a geometric representation of the word's meaning (high cosine similarity → synonyms)

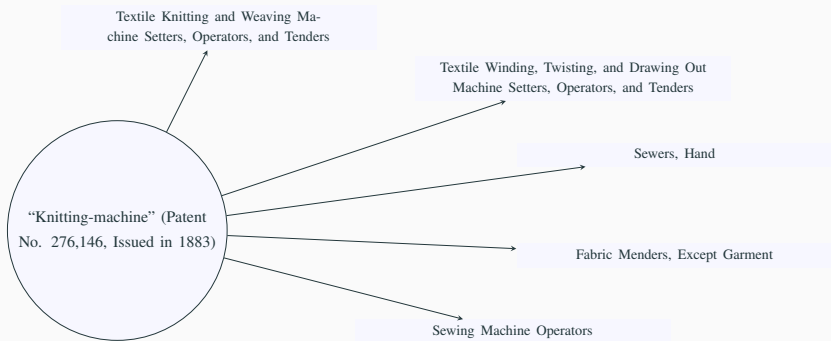
- Use off-the shelf vectors  $x_k$  so we don't need to re-estimate

# Patent-occupation similarity example (1)





## Patent-occupation similarity example (2)



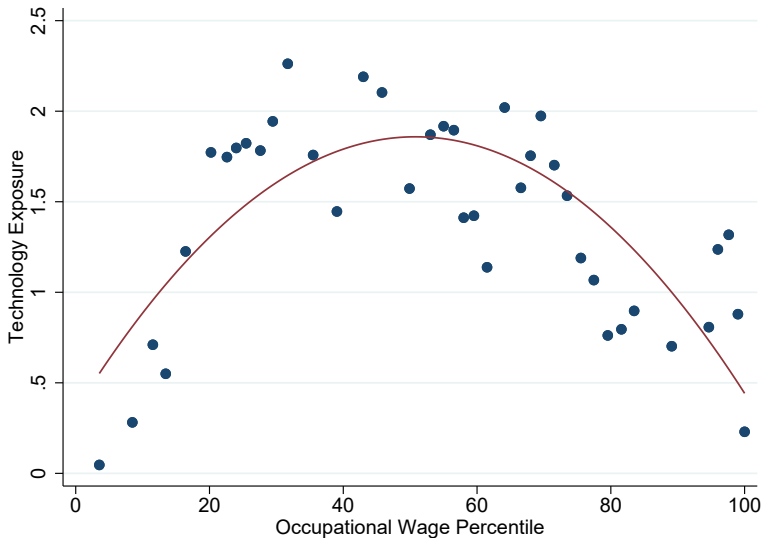
# Identifying variation in technology exposure over time

So far, we have a distance measure between each patent and each occupation. Next step is to construct time-series indices:

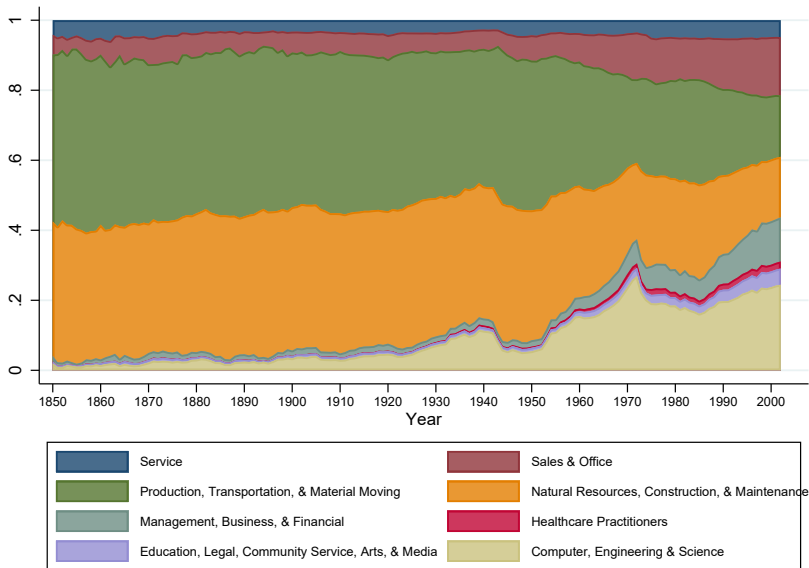
$$\eta_{j,t} = \frac{1}{\kappa_t} \sum_{i \in \Gamma_t} \tilde{\rho}_{i,j} \times \mathbf{1}(\tilde{q}_{i,t} \geq \tilde{q}_{p90})$$

- Focus on set of patents issued in year  $t$  ( $\Gamma_t$ )
- Restrict to breakthrough patents by KPST (quality  $\tilde{q}_{i,t}$  in top 10%)
- For each occupation  $j$ , weight patent  $i$  by its similarity to that occupation (cosine similarity  $\tilde{\rho}_{i,j}$ )
- Scale by population  $\kappa_t$
- Details:
  - ▶ Impose some sparsity on  $\rho$  (set the lowest 80% elements to zero)
  - ▶ To account for shifts in language remove time  $\times$  tech class FEs from  $q$  and  $\rho$ , tilde denotes the adjusted measures

## Middle-skill occupations more exposed to technical change

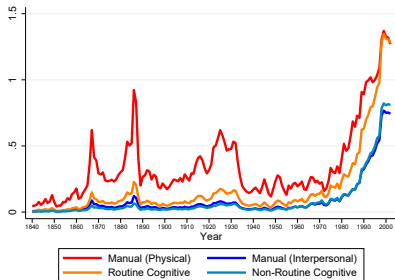


# Technological exposure, by major occupation group

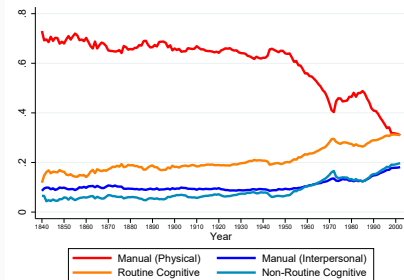


# Technological exposure, by task content

A. Levels



B. Composition



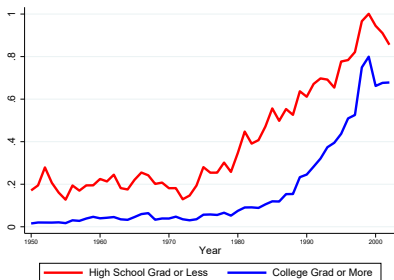
- Figure plots

$$\lambda_{w,t} = \sum_i \eta_{i,t} \times T_w(i) \times \omega_i$$

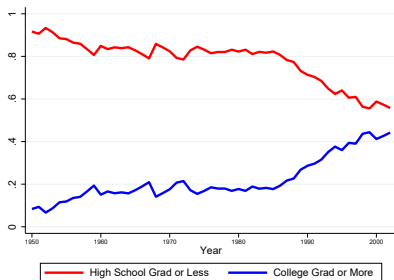
where  $T_w(i)$  be an indicator function that equals 1 if occupation  $i$  has a score in the top quintile across occupations for task  $w$ ,  $\omega_i$  denotes employment shares for occupation  $i$ .

# Technological exposure, by education requirements

A. Levels



B. Composition



- Figure plots

$$\zeta_{s,t} = \sum_i \eta_{i,t} \times S_{s,t}(i) \times \omega_{i,t}$$

where  $S_{s,t}$  is an indicator that takes a value of 1 if occupation  $i$  is in the top quintile of the time  $t$  cross-sectional distribution of shares of workers falling in category  $s$ ,  $\omega_i$  denotes employment shares for occupation  $i$ .

# **Technology and Labor Market Outcomes**

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# Employment and Technology Exposure

Long Run, 1850–present:

	A. Occupation-level Employment				B. Industry X Occupation level employment			
	10 Years	20 Years	10 Years	20 Years	10 Years	20 Years	10 Years	20 Years
Technology Exposure, $\eta_{i,t}$	-0.43*** (-4.68)	-0.75*** (-6.30)	-0.33*** (-4.17)	-0.66*** (-6.33)	-0.37*** (-2.76)	-0.76*** (-3.69)	-0.38*** (-2.83)	-0.86*** (-3.92)
Observations	2,865	2,574	2,492	2,208	102,400	81,009	72,451	54,662
R <sup>2</sup> (Within)	0.016	0.043	0.067	0.078	0.003	0.013	0.004	0.018
Controls								
Time FE	Y	Y	Y	Y				
Industry X Time FE					Y	Y	Y	Y
Lagged Dependent Variable			Y	Y			Y	Y

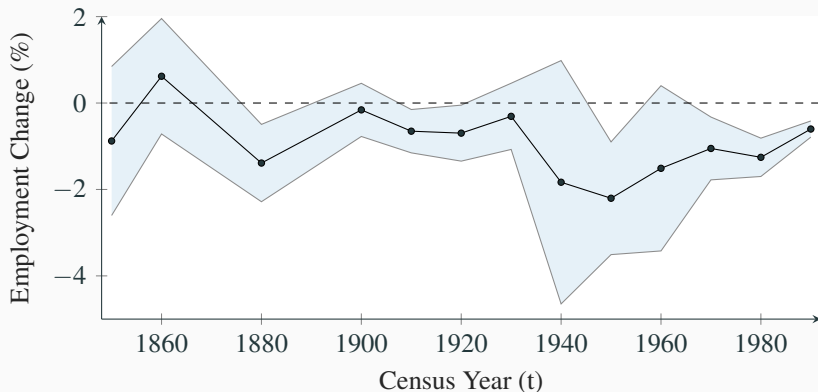
**Note:** The table above reports results from regressions of the form

$$\frac{1}{k} \left( \log Y_{i,t+k} - \log Y_{i,t} \right) = \alpha_0 + \alpha_t + \beta(k)\eta_{i,t} + \rho (\log Y_{i,t} - \log Y_{i,t-k}) + \varepsilon_{i,t}$$

for  $k = 10, 20$  years for Census years spanning from 1850-2010. Here  $Y_{i,t}$  is the occupation's share in total non-farm employment.  $\eta_{i,t}$  is standardized and growth rates are in annualized percentage terms. Standard errors are clustered by occupation and corresponding t-stats are shown in parentheses. Observations are weighted by occupation employment share at time  $t$ .



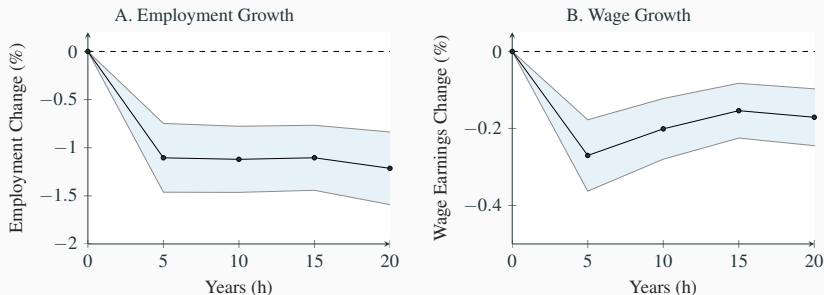
# Employment and Technology Exposure, by decade



**Note:** Figure shows the slope coefficients on annual regressions of 20-Year employment share growth on our technology exposure  $\eta_{i,t}$ , using Census Years from 1850 to 1990. Standard errors are clustered by occupation and shaded area represents the corresponding 90% confidence intervals for  $\beta_{\tau}$ . Growth rates are expressed in annualized percentage terms and  $\eta_{i,t}$  is standardized.

# Employment, wage earnings and technology exposure

Recent period, 1980–present:



**Note:** The Figures above plot coefficients from panel regressions of annualized wage and income growth rates over different time horizons on occupation innovation exposures:

$$y_{i,t+k} - y_{i,t} = \alpha + \beta\eta_{i,t} + \delta X_{i,t} + \varepsilon_{i,t}$$

Controls  $X_{i,t}$  include: three one-year lags of dependent variable, time fixed effects, wage, and occupation employment share. Dependent variable is expressed in annualized percentage terms and  $\eta_{i,t}$  is standardized. Figures plot 90% confidence interval for each time horizon. Data come from the CPS Merged Outgoing Rotation Groups (MORG) and cover the 1985–2018 period.

# Impact of Innovation on Individual Workers, Panel Analysis

We now track the **same workers over time** using a panel of individuals in the CPS linked with their earnings/employment histories in the Detailed Earnings Record (DER).

- Observe occupation and education in year worker is in CPS
  - ▶ Only consider individuals of working age (25-55)
  - ▶ Only include individuals with occupation information  $\leq 5$  years old
- Merge this with annual earnings and employer data from the DER.
- Use Census patent–firm identifier crosswalks to link to patents that originate in the worker’s industry (tech exposure  $\eta$  now varies at occupation-industry level)

# Worker Earnings Data

Calculate growth in age-adjusted average earnings over the next 3-, 5-, and 10-year horizons

- Construct **age-adjusted income** between periods  $t$  and  $t + k$

$$w_{t,t+k}^i \equiv \log \left( \frac{\sum_{j=0}^k W2 \text{ wage}_{i,t+j}}{\sum_{j=0}^k D(\text{age}_{i,t+j})} \right)$$

- Main outcome variable is growth in (cumulative) log earnings

$$Y_{i,t:t+h} \equiv w_{t+1,t+h}^i - w_{t-2,t}^i$$

Our specification emphasizes **permanent** income changes

## Individual workers experience lower wages

	(1)	(2)
<i>A. Cond. Mean, <math>E[g]</math>, by Horizon</i>		
3 years	-1.14 (-5.86)	-1.08 (-4.34)
5 years	-1.51 (-6.15)	-1.29 (-4.13)
10 years	-1.50 (-4.85)	-1.43 (-3.26)
Controls:		
Industry FE	Y	
Occupation FE	Y	
Year FE	Y	
Industry $\times$ Year FE		Y
Occupation $\times$ Year FE		Y

Following a one- $\sigma$  increase in technology exposure, worker's average wages fall about 1.1–1.5%

# Individual workers experience higher labor income risk

	(1)	(2)
<hr/>		
<i>B. Risk: Absolute Income Growth <math>E[ g ]</math></i>		
5 years	0.78	0.45
	(2.43)	(2.16)
<hr/>		
<i>C. Skewness: Prob. Large Income Decline <math>p(g &lt; p^{10})</math></i>		
5 years	0.58	0.41
	(4.76)	(3.31)
<hr/>		
Controls:		
Industry FE	Y	
Occupation FE	Y	
Year FE	Y	
Industry $\times$ Year FE		Y
Occupation $\times$ Year FE		Y
<hr/>		

Following a one- $\sigma$  increase in technology exposure, worker earnings risk increases

# Magnitudes larger for less educated workers

Education	(1)	(2)	(3)	(4)	(5)
	Cond. Mean $E[g]$			St. Dev $E[ g ]$	Skew $p(g < p^{10})$
	3-year	5-year	10-year	5-year	5-year
College	-0.09 (-3.33)	-1.14 (-3.34)	-1.21 (-2.49)	0.49 (2.65)	0.35 (2.57)
No College	-1.30 (-5.58)	-1.50 (-5.18)	-1.76 (-4.47)	0.39 (1.51)	0.48 (4.33)
Coeff. Differences	p-values				
College = No College	0.043	0.110	0.052	0.537	0.071

# Magnitudes larger for older workers

	(1)	(2)	(3)	(4)	(5)
Worker Age	Cond. Mean $E[g]$			St. Dev $E[ g ]$	Skew $p(g < p^{10})$
	3-year	5-year	10-year	5-year	5-year
25–35 years	-0.39 (-1.86)	-0.64 (-2.55)	-0.92 (-2.42)	0.38 (1.84)	0.18 (1.50)
35–45 years	-0.86 (-5.24)	-1.04 (-5.08)	-1.37 (-3.63)	0.05 (0.37)	0.23 (2.55)
45–55 years	-1.95 (-3.72)	-2.25 (-3.55)	-2.51 (-3.02)	1.13 (2.5)	0.88 (3.36)
Coeff. Differences	p-values				
45–55 = 25–35	0.001	0.002	0.006	0.051	0.001
45–55 = 35–45	0.015	0.020	0.044	0.010	0.011



# Magnitudes larger for top earners

Income Percentile	(1)	(2)	(3)	(4)	(5)
	Cond. Mean $E[g]$			St. Dev $E[ g ]$	Skew $p(g < p^{10})$
	3-year	5-year	10-year	5-year	5-year
0 to 25-th	-1.24 (-5.76)	-1.49 (-5.28)	-1.85 (-4.70)	-0.26 (-1.07)	0.29 (2.23)
25 to 50-th	-0.85 (-4.14)	-1.01 (-3.57)	-0.96 (-2.04)	0.10 (0.40)	0.26 (1.45)
50 to 75-th	-1.01 (-3.51)	-1.18 (-3.07)	-1.01 (-1.87)	0.48 (1.65)	0.39 (2.84)
75 to 95-th	-1.05 (-4.12)	-1.17 (-3.45)	-0.81 (-1.64)	0.76 (3.25)	0.39 (2.76)
95 to 100-th	-2.24 (-6.11)	-2.47 (-4.75)	-2.28 (-3.83)	2.01 (5.78)	1.26 (5.50)
Coeff. Differences	p-values				
[95-100] = [25-95]	0.000	0.000	0.002	0.000	0.000
[0-25] = [25-95]	0.701	0.630	0.331	0.175	0.853
[95-100] = [0-25]	0.019	0.092	0.498	0.000	0.000

# Summary

Our technology exposure measure negatively related to worker outcomes

- Correlation between technology exposure and employment is negative at the occupation level
- Correlation between technology exposure and worker wages negative, both at the occupation but also at the worker level. Magnitudes larger for:
  - a. less educated
  - b. older
  - c. **more highly-paid** workers within an occupation-industry

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**Q:** How to square (c) with the standard assumption that skilled labor is more complementary to technology than unskilled labor?

**A:** Skilled workers as a group may benefit, yet individual workers may get left behind.

# Model

---

- Output function of technology  $\xi$ , skilled  $H$  and unskilled  $L$  labor

$$Y_t = \left[ \mu (H_t)^\sigma + (1 - \mu) \left( \lambda (\xi_t)^\rho + (1 - \lambda) (L_t)^\rho \right)^{\sigma/\rho} \right]^{1/\sigma}$$

- ▶ **Standard Assumption:** Skilled labor more complementary to technology than unskilled labor:  $\sigma < \rho < 1$
- Individual workers  $i$  endowed with  $\theta_{i,t}$  units of skilled labor and  $1 - \theta_{i,t}$  units of unskilled labor:

$$H_t = \int_0^1 \theta p_t(\theta) d\theta, \quad L_t = 1 - H_t$$

- Worker earnings:

$$W_{L,t} + \theta_{it} (W_{H,t} - W_{L,t})$$

Arrival of new technologies can render existing skills obsolete:

- With some probability  $\theta_{it}$  falls as technology  $\xi$  improves

$$d\xi_t = -g\xi_t dt + \kappa dN_t.$$

$$d\theta_{i,t} = m\theta_{i,t}dM_{i,t} - h\theta_{i,t}dN_t,$$

- Workers differentially exposed:
  - ▶ Exposure stochastic and i.i.d.  $d \in \{0, 1\}$  with  $Prob(d = 1) = \alpha$

# Implications

- Skill premium  $W_H - W_L$  increases with  $\xi$  due to:
  - ▶ technology-skill complementarity
  - ▶ skill displacement drives up  $W_H$  due to skill scarcity
- Skilled workers **as a group** are relatively better off!
- Yet, individual workers who experience declines in skill  $\theta$  can experience significant income declines.
  - ▶ i.e. membership in the skilled group need not remain constant.
- Depending on the relative strength of these two effects, earnings of (previously) top workers can decline more than lower-paid workers.



# Model Calibration

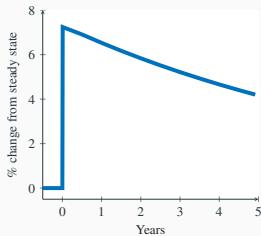
Description	Parameter	Value
Share of workers who do not move up the ladder	$s_l$	0.375
Minimum level of skill	$\underline{\theta}$	0.03
Probability of worker exit	$\delta$	0.025
Amount of skills acquired	$m$	0.03
CES parameter in inner nest (technology $\xi$ and low-skill labor $L$ )	$\rho$	0.74
Share of technology in inner nest	$\lambda$	0.27
CES parameter in outer nest (high-skill labor $H$ and $\xi/L$ composite)	$\sigma$	-0.12
Share of high-skill labor in outer nest	$\mu$	0.17
Size of technology improvement	$\kappa$	0.31
Arrival rate of technology shocks	$\omega$	1.56
Share of exposed workers	$\alpha$	0.32
Human capital loss percentage conditional on fall	$h$	0.06
Rate of depreciation of technology	$g$	0.12
Likelihood of worker skill acquisition	$\phi$	2.40

# Model Fit

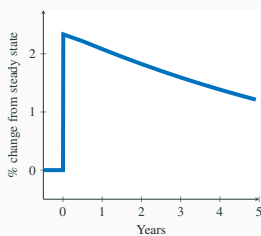
Statistic	Data	Model
Labor share, average	0.66	0.59
Labor share, response to $\xi$	-1.29	-1.48
Skill premium (p75 / p25 ratio), average	2.45	1.68
Labor productivity, response to $\xi$	2.81	2.31
Worker earnings growth response to $\xi$		
0 to 25-th percentile	-1.49	-1.13
25 to 50-th percentile	-1.01	-1.06
50 to 75-th percentile	-1.18	-1.72
75 to 95-th percentile	-1.17	-2.00
95 to 100-th percentile	-2.47	-2.45
Likelihood of large wage declines in response to $\xi$		
0 to 25-th percentile	0.29	0.51
25 to 50-th percentile	0.26	0.51
50 to 75-th percentile	0.39	0.51
75 to 95-th percentile	0.39	0.51
95 to 100-th percentile	1.26	1.40

# Model: Impulse Responses

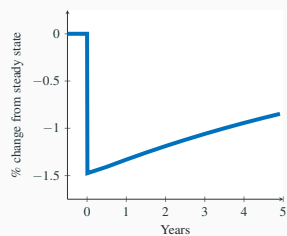
A. Technology  $\xi$



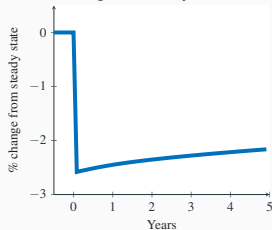
B. Output / Productivity ( $Y$ )



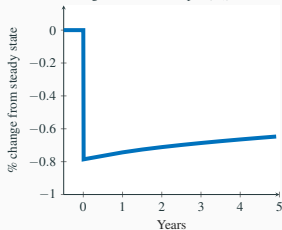
C. Labor Share



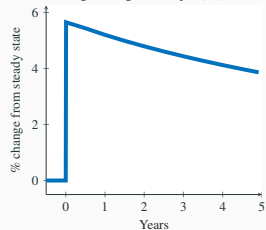
D. High-skill labor input  $H$



E. Wage for low-skill input ( $W_l$ )

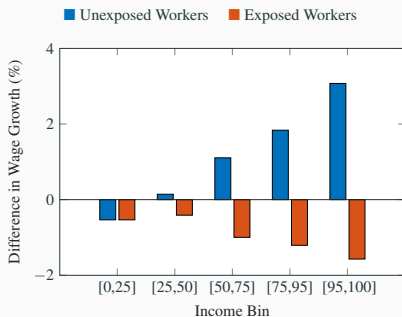


F. Wage for high-skill input ( $W_h$ )

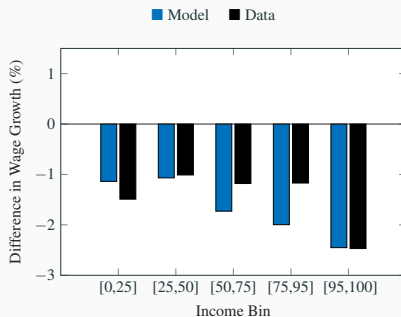


# Model: Innovation and Worker Earnings

A. Differences in Post-Shock Wage Growth



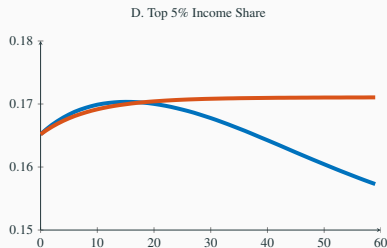
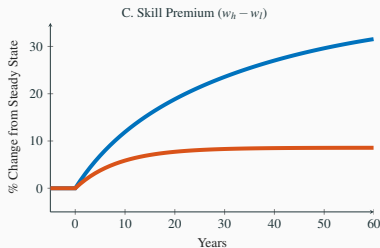
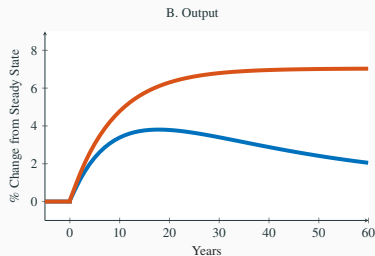
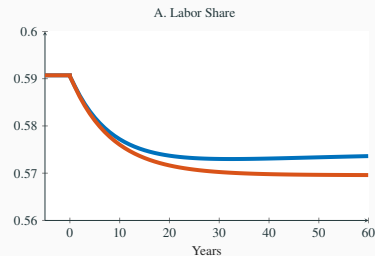
B. Regression Coefficients for Post-Shock Wage Growth



# Technological Innovation and Inequality

- How does an increase in the rate of innovation affect income inequality?
- Two forces in the model:
  - ▶ Increase in skill premium  $\rightarrow$  higher inequality
  - ▶ Higher rate of skill displacement  $\rightarrow$  lower inequality
- To disentangle these two forces in the model, consider the following experiments:
  1. Increase the rate of arrival of technological innovation  $\omega$
  2. In addition, also increase the rate of skill acquisition  $\phi$

# The race between education and technology



Transition paths to new SS: ■ Higher rate of innovation ■ Higher rate of innovation and faster skill acquisition

# Conclusion

- We construct direct measures of technology and relate them to worker outcomes.
- We find that technological improvements are robustly negatively related to worker labor market outcomes, both at the aggregate but also at the individual levels.
  - ▶ Magnitudes larger for (a) less educated, (b) older, and (c) most highly-paid workers within occupation-industry
- Allowing for skill displacement in the standard model of technology-skill complementarity **key** in interpreting these findings
- **Caveat:** We are **not** going to be able to say anything about the creation of new occupations. Our results thus pertain to skill displacement of workers in **existing tasks**. Autor, Salomons, and Seegmiller (2021): role of technological change in the creation of new work.

# Census Acknowledgment

The U.S. Census Bureau reviewed this data product for unauthorized disclosure of confidential information and approved the disclosure avoidance practices applied to this release (approval number CBDRB-FY21-POP001-0176).



# Additional Slides

# Technology And Employment Over the Long Run (1850-2010)– Heterogenous effects by age

	A. Full Sample	B. Sub-samples		
		1850–1920	1930–1960	1970–1990
Age (20–29) $\times$ Technology Exposure, $\eta_{i,t}$	-0.71*** (-3.46)	-2.24*** (-4.08)	-0.073 (-0.19)	-0.58** (-2.33)
Age (30–39) $\times$ Technology Exposure, $\eta_{i,t}$	-0.57*** (-3.41)	-1.70*** (-3.28)	-0.098 (-0.31)	-0.50** (-2.44)
Age (40–49) $\times$ Technology Exposure, $\eta_{i,t}$	-1.10*** (-6.20)	-2.13*** (-4.40)	-0.62* (-1.88)	-1.03*** (-4.85)
Observations	6,512	2,232	1,989	2,291
R <sup>2</sup> (Within)	0.066	0.074	0.055	0.090
Controls				
Age Group X Year FE	Y	Y	Y	Y
Lagged Dependent Variable	Y	Y	Y	Y
P-val (40–49) - (20–29)	0.015	0.776	0.129	0.002