Technology and Labor Markets: Past, Present, and Future; Evidence from Two Centuries of Innovation

H. Liu[1] D. Papanikolaou[1,2] L. Schmidt[3] B. Seegmiller[1]

[1]Kellogg School of Management

[2]NBER

[3]MIT Sloan

Main Goal

Question: Understand how technology improvements affect demand for labor. Challenges:

1. Technology can complement or substitute for labor in individual tasks.
2. Yet, even labor-saving technologies can increase demand for a specific occupation if
   - Technology substitutes for only a narrow set of tasks; workers can reallocate effort.
   - Increase overall labor demand at the sector level.

What we do: Disentangle these channels using a combination of theory and data.

Summary of Findings

Our Approach: Create theoretically-grounded measures of technology exposure that vary by occupation and decade.

Summary of Findings

Our Approach: Create theoretically-grounded measures of technology exposure that vary by occupation and decade. Model implies that direct effect of technology exposure on labor demand depends on two sufficient statistics:

Summary of Findings

Our Approach: Create theoretically-grounded measures of technology exposure that vary by occupation and decade. Model implies that direct effect of technology exposure on labor demand depends on two sufficient statistics:

1. The mean exposure of an occupation's tasks to technology.

Summary of Findings

Our Approach: Create theoretically-grounded measures of technology exposure that vary by occupation and decade. Model implies that direct effect of technology exposure on labor demand depends on two sufficient statistics:

1. The mean exposure of an occupation's tasks to technology.
2. The concentration of exposure into specific tasks.

Summary of Findings

Our Approach: Create theoretically-grounded measures of technology exposure that vary by occupation and decade. Model implies that direct effect of technology exposure on labor demand depends on two sufficient statistics:

1. The mean exposure of an occupation's tasks to technology.
2. The concentration of exposure into specific tasks.

Summary of Findings

Our Approach: Create theoretically-grounded measures of technology exposure that vary by occupation and decade. Model implies that direct effect of technology exposure on labor demand depends on two sufficient statistics:

1. The mean exposure of an occupation's tasks to technology.
2. The concentration of exposure into specific tasks.

Main Finding: Technological change over the last century has increased relative demand for occupations that employ relatively more highly educated workers, more women, and paid higher wages.

Summary of Findings

Our Approach: Create theoretically-grounded measures of technology exposure that vary by occupation and decade. Model implies that direct effect of technology exposure on labor demand depends on two sufficient statistics:

1. The mean exposure of an occupation's tasks to technology.
2. The concentration of exposure into specific tasks.

Main Finding: Technological change over the last century has increased relative demand for occupations that employ relatively more highly educated workers, more women, and paid higher wages.

Speculation: Improvements in AI will partly reverse these relative shifts.

Model Setup

Production:

CES Layer	EoS
Industries $\rightarrow$ Aggregate Output	θ
Occupations $\rightarrow$ Industries	χ
Tasks $\rightarrow$ Occupations	ψ
Capital and Labor $\rightarrow$ Tasks	ν

Model Setup

Production:

CES Layer	EoS
Industries $\rightarrow$ Aggregate Output	θ
Occupations $\rightarrow$ Industries	χ
Tasks $\rightarrow$ Occupations	ψ
Capital and Labor $\rightarrow$ Tasks	ν

Technological Innovation:

1. Decline in the quality-adjusted price of capital

$$\Delta \log q(j) = -\varepsilon(j).$$

2. New Products: Increases in number of products α_I at industry level.

Labor Supply

Within job: A worker chooses hours $h(j)$ across tasks j

$$l(j) = h(j)^{1-\beta} \qquad \text{subject to} \qquad \sum_j h(j) = 1$$

Labor Supply

Within job: A worker chooses hours $h(j)$ across tasks j

$$l(j) = h(j)^{1-\beta} \qquad \text{subject to} \qquad \sum_j h(j) = 1$$

Across jobs: Workers' labor supply to job (o, I) function of job-specific wage index

Microfoundation: occupation-specific taste shocks, as in Lamadon-Mogstad-Setzler (2022)

Technology and Labor Demand: Mean Exposure

$$\boxed{\Delta \log N(o,f) \approx \zeta \, \eta_m \, m(\varepsilon) + \zeta \, \frac{1}{2\beta} \, \eta_o^2 \, C(\varepsilon) + \text{Spillovers}}$$

Technology and Labor Demand: Mean Exposure

$$\boxed{\Delta \log N(o,f) \approx \zeta \eta_m m(\varepsilon) + \zeta \frac{1}{2\beta} \eta_o^2 C(\varepsilon) + \text{Spillovers}}$$

1. Mean technology improvement across tasks:

$$m(\varepsilon) \equiv \frac{1}{J} \sum_{j \in J} \varepsilon(j)$$

Technology and Labor Demand: Mean Exposure

$$\boxed{\Delta \log N(o,f) \approx \zeta \eta_m m(\varepsilon) + \zeta \frac{1}{2\beta} \eta_o^2 C(\varepsilon) + \text{Spillovers}}$$

1. Mean technology improvement across tasks:

$$m(\varepsilon) \equiv \frac{1}{J} \sum_{j \in J} \varepsilon(j)$$

Impact of mean exposure on labor demand:

$$\eta_m \equiv -\frac{s_k (\nu - \chi)}{\zeta + \nu s_k + \chi (1 - s_k)}$$

Sign depends on the elasticity between capital and labor vs elasticity across occupations

Technology and Labor Demand: Gains from Reallocation

$$\boxed{\Delta \log N(o,f) \approx \zeta \eta_m m(\varepsilon) + \zeta \frac{1}{2\beta} \eta_o^2 C(\varepsilon) + \text{Spillovers}}$$

2. Concentration of improvements to specific tasks:

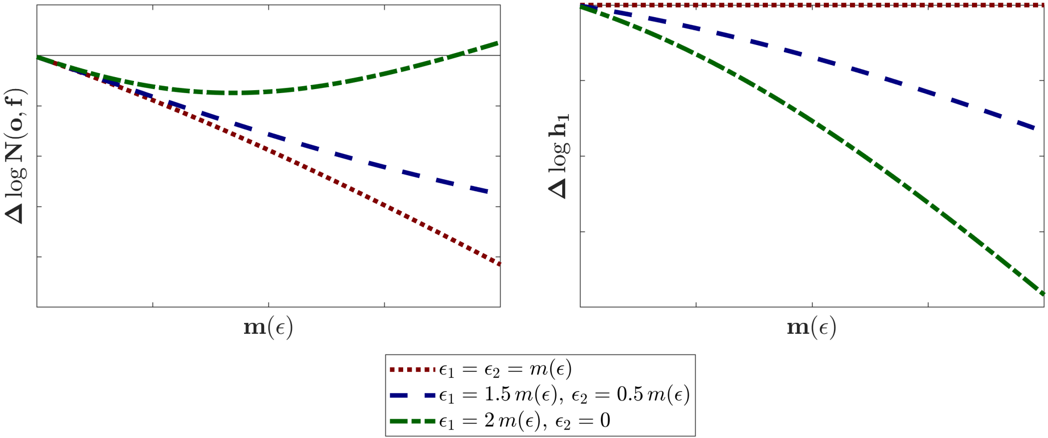
$$C(\varepsilon) \equiv \frac{1}{J} \sum_{j \in J} \Big(\varepsilon(j) - m(\varepsilon) \Big)^2$$

Impact depends on flexibility of hours reallocation $(1/\beta)$ and η_o

$$\eta_o \equiv -\frac{s_k \beta (\nu - \psi)}{(1-\beta) + \beta (\nu s_k + \psi (1 - s_k))}$$

η_o captures magnitude of cross-task spillovers of technology improvements

Technology and Labor Demand: Gains from Reallocation



Technology and Labor Demand: Spillovers

$$\boxed{\Delta \log N(o,f) \approx \zeta \eta_m m(\varepsilon) + \zeta \frac{1}{2\beta} \eta_o^2 C(\varepsilon) + \underbrace{\Delta \log \alpha_I + \zeta \eta_z \Delta_\varepsilon \log Z_I}_{\text{Industry Spillovers}} + \underbrace{\frac{\zeta \eta_z}{\theta - \chi} \Delta_\varepsilon \log \bar{\Omega}}_{\text{Aggregate Spillovers}}}$$

Technology and Labor Demand: Spillovers

$$\boxed{\Delta \log N(o,f) \approx \zeta \eta_m m(\varepsilon) + \zeta \frac{1}{2\beta} \eta_o^2 C(\varepsilon) + \underbrace{\Delta \log \alpha_I + \zeta \eta_z \Delta_\varepsilon \log Z_I}_{\text{Industry Spillovers}} + \underbrace{\frac{\zeta \eta_z}{\theta - \chi} \Delta_\varepsilon \log \bar{\Omega}}_{\text{Aggregate Spillovers}}}$$

3. Industry Spillovers depend on

Technology and Labor Demand: Spillovers

$$\boxed{\Delta \log N(o,f) \approx \zeta \eta_m m(\varepsilon) + \zeta \frac{1}{2\beta} \eta_o^2 C(\varepsilon) + \underbrace{\Delta \log \alpha_I + \zeta \eta_z \Delta_\varepsilon \log Z_I}_{\text{Industry Spillovers}} + \underbrace{\frac{\zeta \eta_z}{\theta - \chi} \Delta_\varepsilon \log \bar{\Omega}}_{\text{Aggregate Spillovers}}}$$

3. Industry Spillovers depend on

a) New products $\longrightarrow$ increase labor demand at industry.

Technology and Labor Demand: Spillovers

$$\boxed{\Delta \log N(o,f) \approx \zeta \eta_m m(\varepsilon) + \zeta \frac{1}{2\beta} \eta_o^2 C(\varepsilon) + \underbrace{\Delta \log \alpha_I + \zeta \eta_z \Delta_\varepsilon \log Z_I}_{\text{Industry Spillovers}} + \underbrace{\frac{\zeta \eta_z}{\theta - \chi} \Delta_\varepsilon \log \bar{\Omega}}_{\text{Aggregate Spillovers}}}$$

3. Industry Spillovers depend on

a) New products $\rightarrow$ increase labor demand at industry.

b) Declines in unit cost of production, whose impact on labor demand depends on

$$\eta_z \equiv \frac{\theta - \chi}{s_k \nu + s_l \chi + \zeta}.$$

Technology and Labor Demand: Spillovers

$$\boxed{\Delta \log N(o,f) \approx \zeta \eta_m m(\varepsilon) + \zeta \frac{1}{2\beta} \eta_o^2 C(\varepsilon) + \underbrace{\Delta \log \alpha_I + \zeta \eta_z \Delta_\varepsilon \log Z_I}_{\text{Industry Spillovers}} + \underbrace{\frac{\zeta \eta_z}{\theta - \chi} \Delta_\varepsilon \log \bar{\Omega}}_{\text{Aggregate Spillovers}}}$$

3. Industry Spillovers depend on

a) New products $\longrightarrow$ increase labor demand at industry.

b) Declines in unit cost of production, whose impact on labor demand depends on

$$\eta_z \equiv \frac{\theta - \chi}{s_k \nu + s_l \chi + \zeta}.$$

4. Aggregate Spillovers: Impossible to identify empirically; focus on **relative labor demand**

Empirical Strategy

Construct direct empirical analogues of key model objects using text of new technologies (patents) and occupation task descriptions.

Empirical Strategy

Construct direct empirical analogues of key model objects using text of new technologies (patents) and occupation task descriptions.

Lots of details, but in a nutshell:

Empirical Strategy

Construct direct empirical analogues of key model objects using text of new technologies (patents) and occupation task descriptions.

Lots of details, but in a nutshell:

1. Estimate the mean similarity of task j to patents in decade T

Empirical Strategy

Construct direct empirical analogues of key model objects using text of new technologies (patents) and occupation task descriptions.

Lots of details, but in a nutshell:

1. Estimate the mean similarity of task j to patents in decade T
2. Use (1) to construct estimates of $m(\varepsilon)$ and $C(\varepsilon)$ at occupation–decade level.

Empirical Strategy

Construct direct empirical analogues of key model objects using text of new technologies (patents) and occupation task descriptions.

Lots of details, but in a nutshell:

1. Estimate the mean similarity of task j to patents in decade T
2. Use (1) to construct estimates of $m(\varepsilon)$ and $C(\varepsilon)$ at occupation–decade level.
3. Measure industry spillovers based on growth in # of patents relevant to each industry.

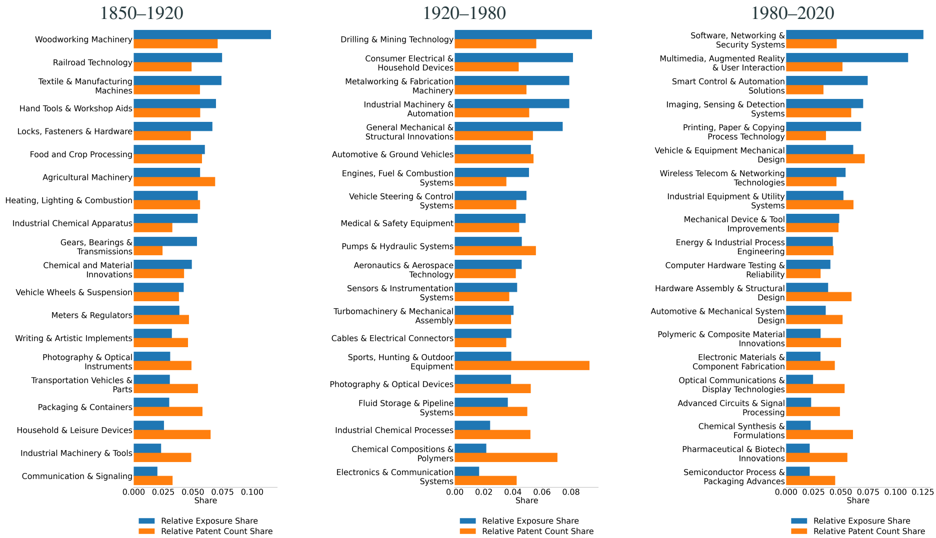
Empirical Strategy

Construct direct empirical analogues of key model objects using text of new technologies (patents) and occupation task descriptions.

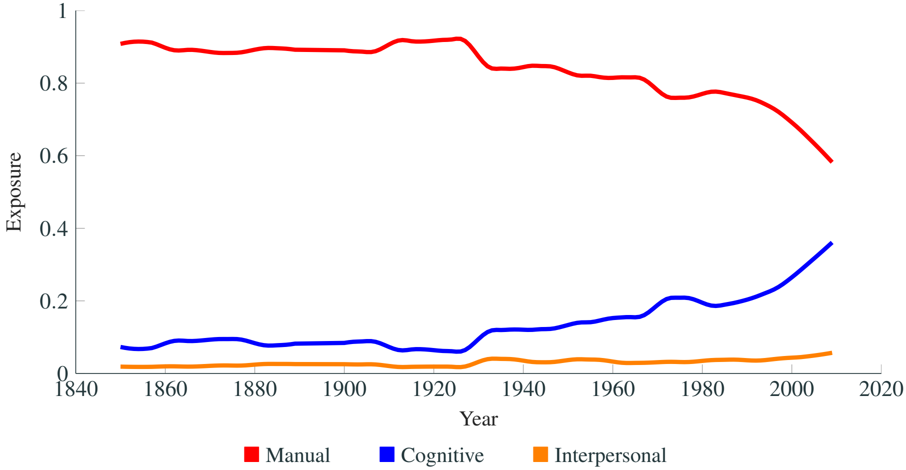
Lots of details, but in a nutshell:

1. Estimate the mean similarity of task j to patents in decade T
2. Use (1) to construct estimates of $m(\varepsilon)$ and $C(\varepsilon)$ at occupation–decade level.
3. Measure industry spillovers based on growth in # of patents relevant to each industry.
4. Direction of technology endogenous; construct shift-share IV based on breakthrough innovations in ‘upstream’ technology classes.

Which Technologies Drive Worker Exposure?



Composition of Overall Technology Exposure, by Task Type



Note: This figure plots the composition of technology exposure by each task type $\tau \in \{\text{Manual, Cognitive, Interpersonal}\}$. The composition of each type-τ task, c_τ, is defined as the share of all valid patent-task link that are contributed by type-τ tasks.

Technology Exposure and Labor Demand

Employment Growth (%)	A. IV			
	10 Years		20 Years	
	(1)	(2)	(3)	(4)
Mean Task Exposure	-8.08***	-8.25***	-16.2***	-16.2***
	(2.06)	(2.06)	(3.21)	(3.23)
Concentration in Task Exposure	4.06**	4.10**	8.44***	8.59***
	(1.88)	(1.90)	(2.83)	(2.84)
Industry Spillovers	44.5**	43.3**	15.3*	19.1**
	(20.39)	(17.18)	(7.94)	(7.40)
N	135,637	135,637	125,956	125,956
Year FE	X		X	
Sector FE	X		X	
Year $\times$ Sector FE		X		X
Employment Share, Lag	X	X	X	X

Summary and Next Steps

So far: Model highlighting three key forces in how technology shapes labor demand:

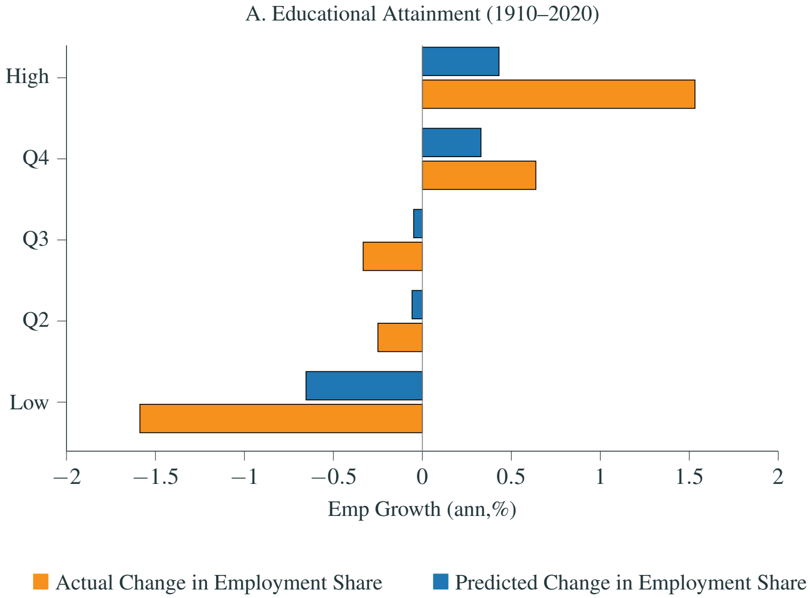
1. Mean exposure of worker tasks to technology.
2. Degree to which exposure is concentrated in specific tasks.
3. Increases in labor demand due to productivity improvements and/or new products.

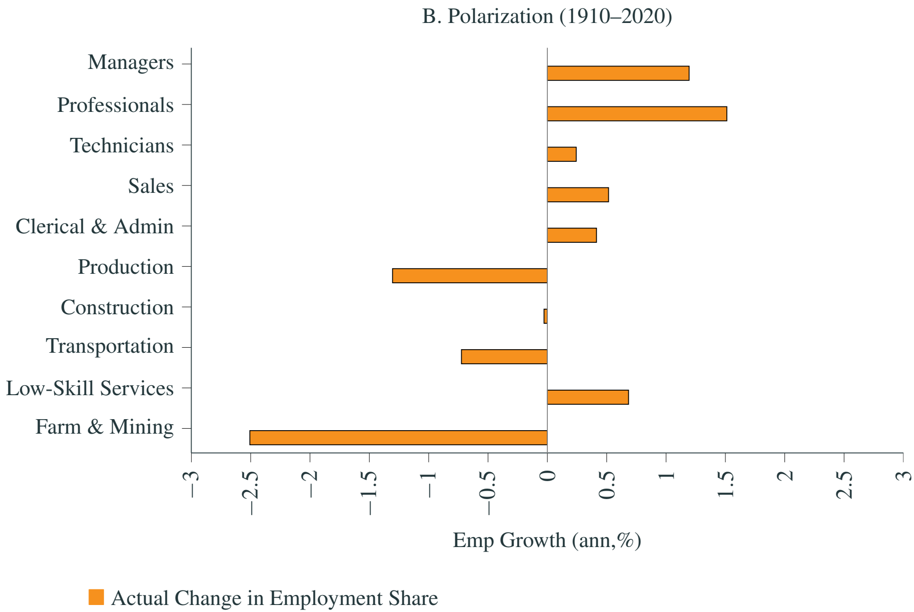
Empirical evidence supports all three mechanisms.

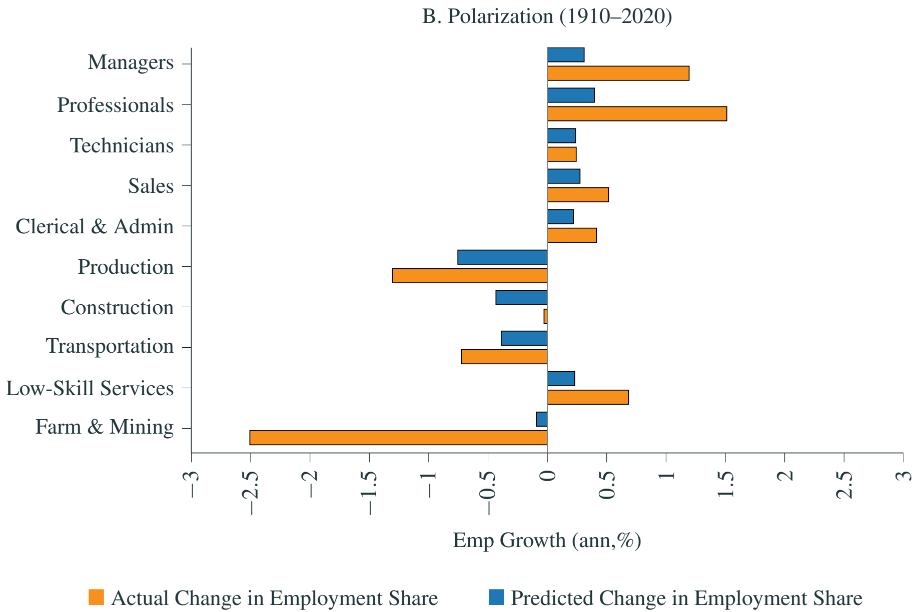
Next: What was the combined effect of these three channels in shaping labor demand?

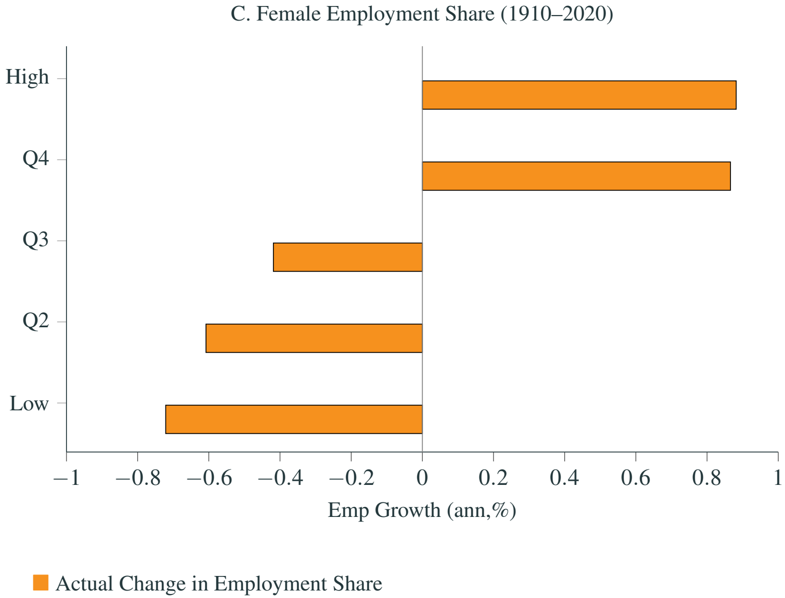
Caveat: Missing intercept problem, so can only discuss shifts in relative labor demand.

A. Educational Attainment (1910–2020)


A. Educational Attainment (1910–2020)
High
Q4
Q3
Q2
Low
−2
−1.5
−1
−0.5
0
0.5
1
1.5
2
Emp Growth (ann,%)
Actual Change in Employment Share
Predicted Change in Employment Share

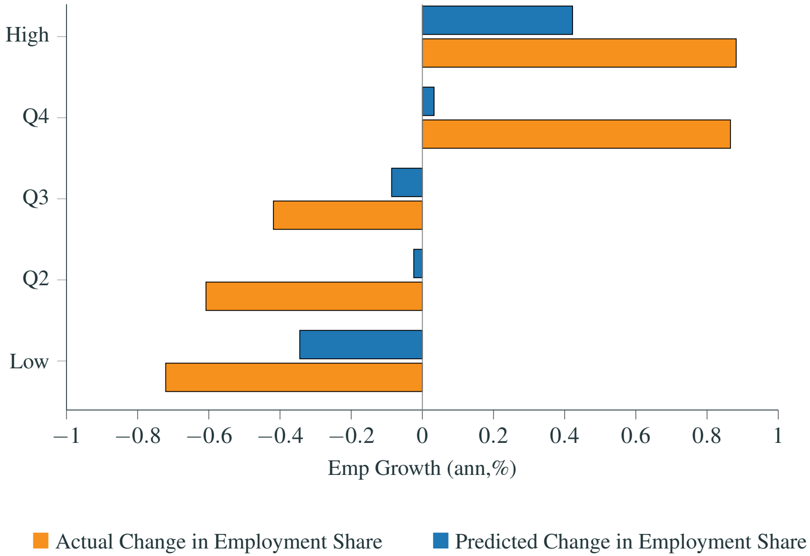

B. Polarization (1910–2020)
Managers
Professionals
Technicians
Sales
Clerical & Admin
Production
Construction
Transportation
Low-Skill Services
Farm & Mining
−3
−2.5
−2
−1.5
−1
−0.5
0
0.5
1
1.5
2
2.5
3
Emp Growth (ann,%)
Actual Change in Employment Share


B. Polarization (1910–2020)
Managers
Professionals
Technicians
Sales
Clerical & Admin
Production
Construction
Transportation
Low-Skill Services
Farm & Mining
−3
−2.5
−2
−1.5
−1
−0.5
0
0.5
1
1.5
2
2.5
3
Emp Growth (ann,%)
Actual Change in Employment Share
Predicted Change in Employment Share



C. Female Employment Share (1910–2020)
High
Q4
Q3
Q2
Low
−1
−0.8
−0.6
−0.4
−0.2
0
0.2
0.4
0.6
0.8
1
Emp Growth (ann,%)
Actual Change in Employment Share

C. Female Employment Share (1910–2020)



Looking Ahead: AI

Model seems consistent with the 1910–2020 experience. What does it imply about impact of AI?

Looking Ahead: AI

Model seems consistent with the 1910–2020 experience. What does it imply about impact of AI?
Take some elasticities from literature, but need to take a stance on the following:

Which tasks can be substituted by AI?

Looking Ahead: AI

Model seems consistent with the 1910–2020 experience. What does it imply about impact of AI?
Take some elasticities from literature, but need to take a stance on the following:

Which tasks can be substituted by AI?

Assumption: AI can (imperfectly) substitute for labor in all cognitive tasks that require less than five years of experience

Looking Ahead: AI

Model seems consistent with the 1910–2020 experience. What does it imply about impact of AI?

Take some elasticities from literature, but need to take a stance on the following:

Which tasks can be substituted by AI?

Assumption: AI can (imperfectly) substitute for labor in all cognitive tasks that require less than five years of experience

How much will the relative price of AI decline?

Looking Ahead: AI

Model seems consistent with the 1910–2020 experience. What does it imply about impact of AI? Take some elasticities from literature, but need to take a stance on the following:

Which tasks can be substituted by AI?

Assumption: AI can (imperfectly) substitute for labor in all cognitive tasks that require less than five years of experience

How much will the relative price of AI decline?

Assumption: Relative price will decline by a similar amount as the decline in the relative price of computers during 1984–2015.

Looking Ahead: AI

Model seems consistent with the 1910–2020 experience. What does it imply about impact of AI? Take some elasticities from literature, but need to take a stance on the following:

Which tasks can be substituted by AI?

Assumption: AI can (imperfectly) substitute for labor in all cognitive tasks that require less than five years of experience

How much will the relative price of AI decline?

Assumption: Relative price will decline by a similar amount as the decline in the relative price of computers during 1984–2015.

How much AI boost industry labor demand?

Looking Ahead: AI

Model seems consistent with the 1910–2020 experience. What does it imply about impact of AI? Take some elasticities from literature, but need to take a stance on the following:

Which tasks can be substituted by AI?

Assumption: AI can (imperfectly) substitute for labor in all cognitive tasks that require less than five years of experience

How much will the relative price of AI decline?

Assumption: Relative price will decline by a similar amount as the decline in the relative price of computers during 1984–2015.

How much AI boost industry labor demand?

Assumption: AI will create new products and hence expand industry demand; calibrate based on data on AI patents and patent-to-product elasticities from Argente et al. (2025)

Looking Ahead: AI

Model seems consistent with the 1910–2020 experience. What does it imply about impact of AI?
Take some elasticities from literature, but need to take a stance on the following:

Which tasks can be substituted by AI?
Assumption: AI can (imperfectly) substitute for labor in all cognitive tasks that require less than five years of experience

How much will the relative price of AI decline?
Assumption: Relative price will decline by a similar amount as the decline in the relative price of computers during 1984–2015.

How much AI boost industry labor demand?
Assumption: AI will create new products and hence expand industry demand; calibrate based on data on AI patents and patent-to-product elasticities from Argente et al. (2025)

Elasticity of substitution ν between AI and Labor?

Looking Ahead: AI

Model seems consistent with the 1910–2020 experience. What does it imply about impact of AI?
Take some elasticities from literature, but need to take a stance on the following:

Which tasks can be substituted by AI?
Assumption: AI can (imperfectly) substitute for labor in all cognitive tasks that require less than five years of experience

How much will the relative price of AI decline?
Assumption: Relative price will decline by a similar amount as the decline in the relative price of computers during 1984–2015.

How much AI boost industry labor demand?
Assumption: AI will create new products and hence expand industry demand; calibrate based on data on AI patents and patent-to-product elasticities from Argente et al. (2025)

Elasticity of substitution ν between AI and Labor?
Assumption: Use empirical estimates from 1910–2020 sample to back out $\nu = 4.63$.

Looking Ahead: AI

Model seems consistent with the 1910–2020 experience. What does it imply about impact of AI? Take some elasticities from literature, but need to take a stance on the following:

Which tasks can be substituted by AI?

Assumption: AI can (imperfectly) substitute for labor in all cognitive tasks that require less than five years of experience

How much will the relative price of AI decline?

Assumption: Relative price will decline by a similar amount as the decline in the relative price of computers during 1984–2015.

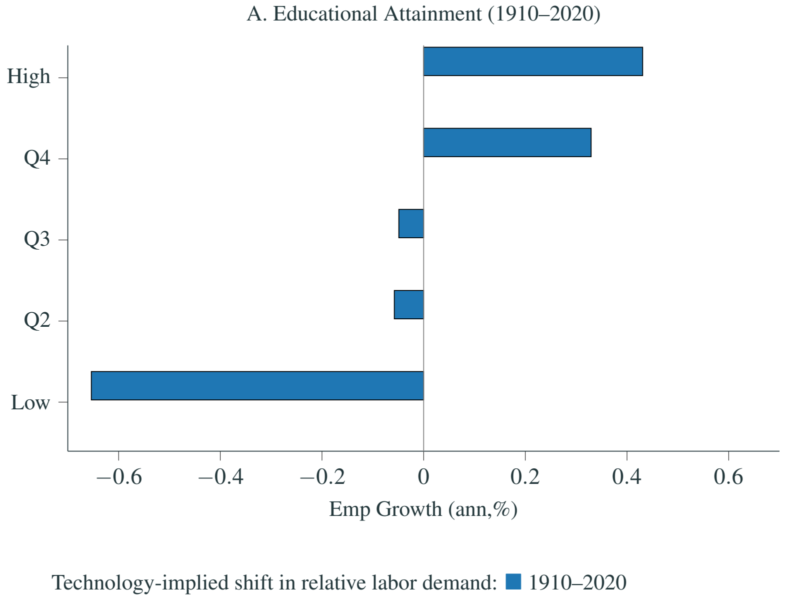
How much AI boost industry labor demand?

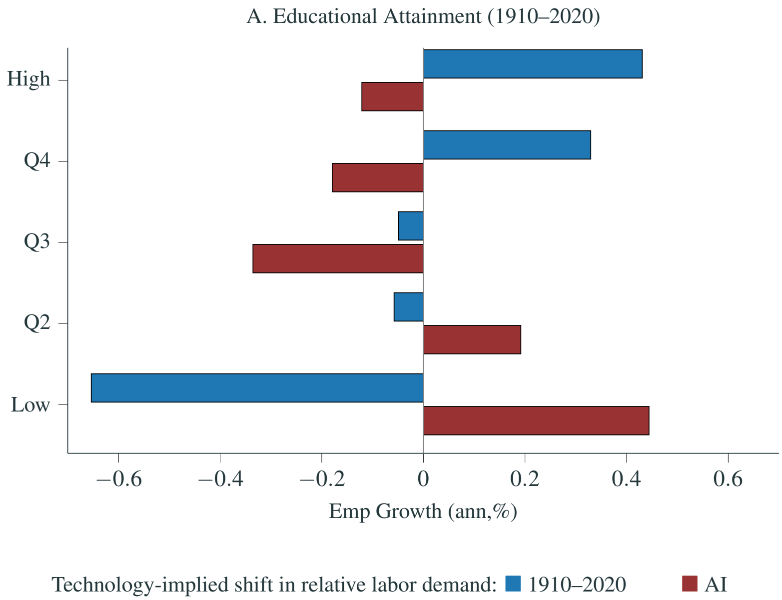
Assumption: AI will create new products and hence expand industry demand; calibrate based on data on AI patents and patent-to-product elasticities from Argente et al. (2025)

Elasticity of substitution ν between AI and Labor?

Assumption: Use empirical estimates from 1910–2020 sample to back out $\nu = 4.63$.

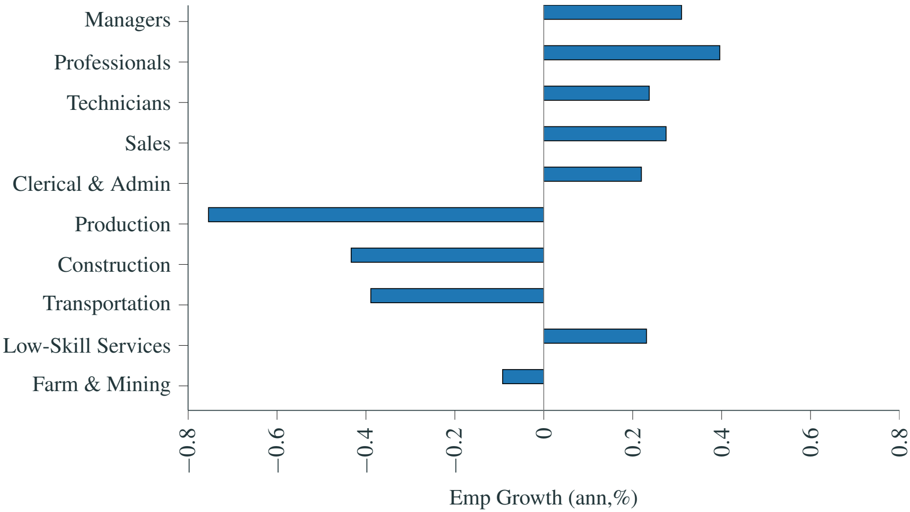
Important Caveat: No GE effects; purely predictions about relative labor demand.


A. Educational Attainment (1910–2020)
High
Q4
Q3
Q2
Low
−0.6
−0.4
−0.2
0
0.2
0.4
0.6
Emp Growth (ann,%)
Technology-implied shift in relative labor demand: 1910–2020



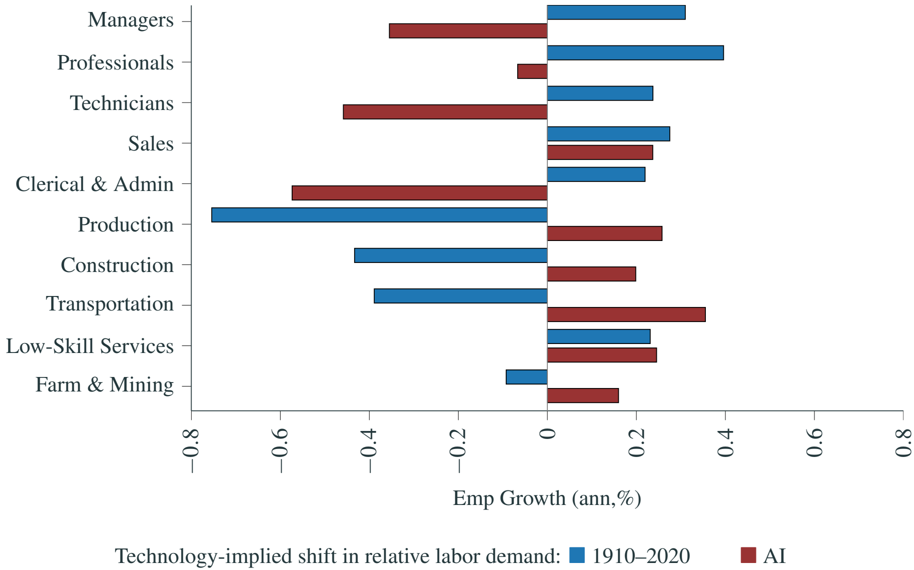
A. Educational Attainment (1910–2020)
High
Q4
Q3
Q2
Low
−0.6
−0.4
−0.2
0
0.2
0.4
0.6
Emp Growth (ann,%)
Technology-implied shift in relative labor demand:
1910–2020
AI

B. Polarization (1910–2020)

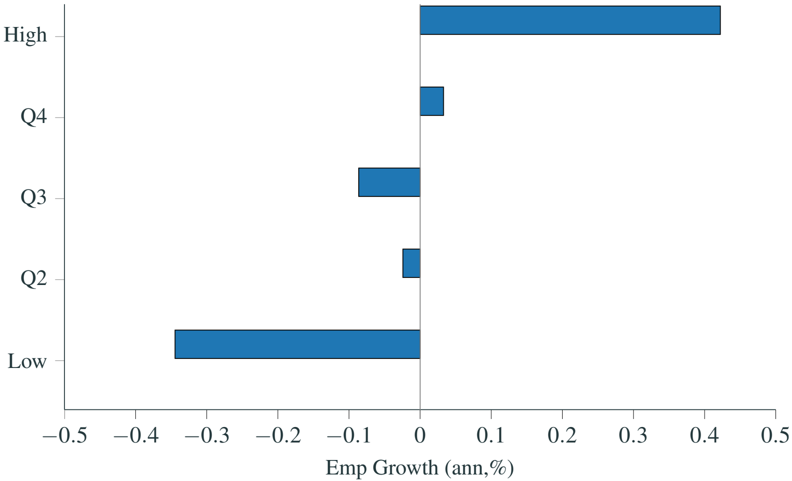


Technology-implied shift in relative labor demand: 1910–2020

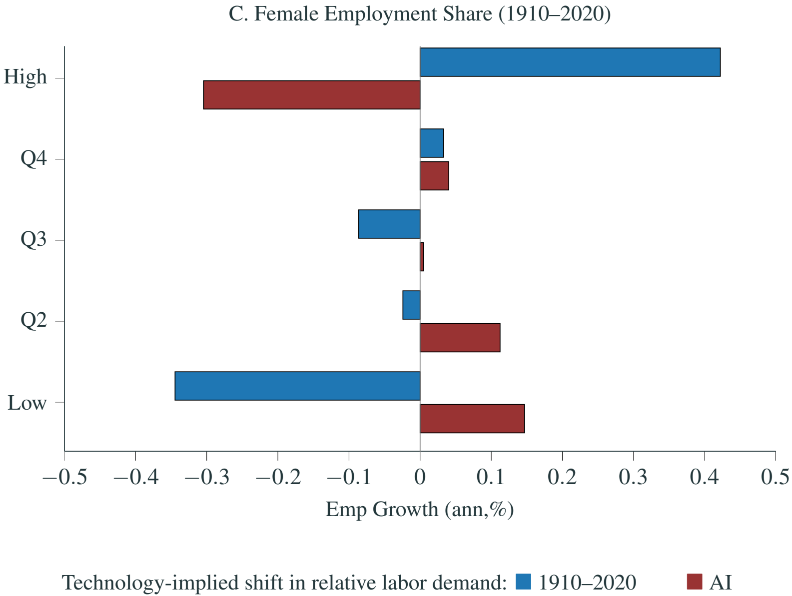
B. Polarization (1910–2020)



C. Female Employment Share (1910–2020)



Technology-implied shift in relative labor demand: 1910–2020


C. Female Employment Share (1910–2020)
High
Q4
Q3
Q2
Low
–0.5
–0.4
–0.3
–0.2
–0.1
0
0.1
0.2
0.3
0.4
0.5
Emp Growth (ann,%)
Technology-implied shift in relative labor demand:
1910–2020
AI

Summary

Technology task exposure need not lead to decline in labor demand.

Our estimates suggest that direction of technological progress over the 1910–2020 period has consistently increased demand for ‘high-skill’ occupations and those with a larger share of female workers.

AI advances over the medium run are likely to reverse these trends.