

# Skill Premium in Times of Rapid Technological Change

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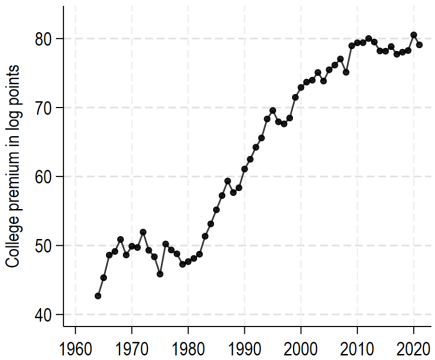
Views are our own, not of the STL Fed/Fed System.

# Motivation




- Rise in College premium: 50 log points in 1980, 80 in 2010, then flattened.
  - Steeper increase in densest areas.
- Existing theories: structural shifts favoring skill.
  - Skill-biased technical change, capital-skill complementarity, automation, and IT.
- **This paper**:
  - Use new job-level data on technology creation and use.
  1. Skill premium depends on the pace of **technology creation** and **standardization**.
  2. Measured technology creation explains variation in skill premia over time, space, and cohorts.

# A Model of Technologies and the Skill Premium

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- Production for a Technology of Age $u$ at time $t$:

$$y_t(u) \;=\; A(b) \;\cdot\; z(u) \;\cdot\; \Big[\alpha(u)^{\frac{1}{\gamma}}\, h_t(u)^{\frac{\gamma-1}{\gamma}} \;+\; \big(1-\alpha(u)\big)^{\frac{1}{\gamma}}\, \ell_t(u)^{\frac{\gamma-1}{\gamma}}\Big]^{\frac{\gamma}{\gamma-1}}.$$

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$$A(b) \;=\; A_0\, e^{gb}, \quad g > 0.$$

- **CES Aggregation ($\sigma > 1$)**

$$Y_t \;=\; \Big(\int_0^{\infty} m_t(u)\, y_t(u)^{\frac{\sigma-1}{\sigma}}\, du\Big)^{\frac{\sigma}{\sigma-1}}.$$

# Equilibrium Conditions: Solving for $(W_H, W_L, Y_t)$

Three market clearing conditions to solve for $(W_H, W_L, Y_t)$.

**(1) Income Clearance**

$$1 = \int_0^\infty m_t(u) \left( \frac{c\left(\alpha(u), W_{h,t}, W_{\ell,t}\right)}{A(t-u)\, z(u)} \right)^{1-\sigma} du,$$

**(2) College Labor Market Clearance**

$$W_{h,t}\, h = Y_t \int_0^\infty m_t(u) \left( \frac{c(\cdot)}{A(t-u)\, z(u)} \right)^{1-\sigma} \alpha(u) \left( \frac{W_{h,t}}{c(\cdot)} \right)^{1-\gamma} du.$$

**(3) Non-College Labor Market Clearance**

$$W_{\ell,t}\, \ell = Y_t \int_0^\infty m_t(u) \left( \frac{c(\cdot)}{A(t-u)\, z(u)} \right)^{1-\sigma} \left[ 1 - \alpha(u) \right] \left( \frac{W_{\ell,t}}{c(\cdot)} \right)^{1-\gamma} du.$$

# Proposition 1/2: Skill Premium in the Long-run (along BGP)

*Consider a BGP with the pace of technology creation is constant, i.e. $m(b) = m$.*

- No change in age distribution of technologies along BGP.
- Special case: $\gamma = \sigma$, skill premium:

$$\frac{W_h}{W_\ell} = \left( \frac{\int_0^\infty e^{-[\delta+(\sigma-1)g]u} \cdot z(u)^{\sigma-1} \cdot \alpha(u)\, du}{\int_0^\infty e^{-[\delta+(\sigma-1)g]u} \cdot z(u)^{\sigma-1} \cdot (1-\alpha(u))\, du} \right)^{\frac{1}{\sigma}} \cdot \left( \frac{h}{\ell} \right)^{-\frac{1}{\sigma}}$$

- **Long-run skill premium**:
  - Independent of $m$
  - Depends on pace of standardization, $\alpha(u)$, vs gaining or losing market share, $z(u)$
  - Supply of skills $\frac{h}{\ell}$

# Proposition 2/2: Skill premium in the Short-run (transition path)

*Consider a permanent or temporary increase in $m(b)$ at $t_0$ from $m$ to $m' > m$.*

- Both generate a temporary shift in tech age distribution towards younger techs.
- Special case: $\gamma = \sigma$, skill premium:

$$\frac{W_{h,t}}{W_{\ell,t}} = \left( \frac{\int_0^\infty m_t(u) \cdot e^{-[\delta+(\sigma-1)g]u} \cdot z(u)^{\sigma-1} \cdot \alpha(u)\, du}{\int_0^\infty m_t(u) \cdot e^{-[\delta+(\sigma-1)g]u} \cdot z(u)^{\sigma-1} \cdot (1-\alpha(u))\, du} \right)^{\frac{1}{\sigma}} \cdot \left( \frac{h}{\ell} \right)^{-\frac{1}{\sigma}}$$

- **Temporary increase in skill premium**, and more persistent if

*i.* Low standardization rate : $\alpha(u)$ decreases slowly.

*ii.* Slow obsolescence: $e^{-[\delta+(\sigma-1)g]u} \cdot z(u)^{\sigma-1}$ decreases slowly.

# Three Empirical Facts

# Technologies Data & Arrival Rate

**Data Construction:**

- Adjust Kalyani et. al. (2025) methodology minimally to allow use of data back to 1930.
- Extract bigrams newly appearing in patents.
- Match each bigram to a Wikipedia page and keep it if that page describes a technology.
- Group matched bigrams into "technologies" (title of the Wikipedia page).
- Assign emergence years based on accelerated incidence in patenting.
- Track in Lightcast job postings (2010-2023)

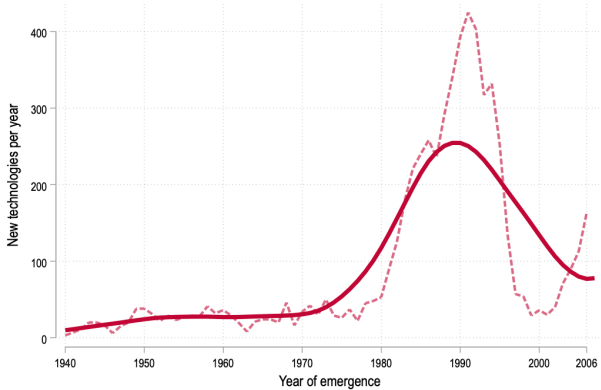
Wikipedia | Patent examples | Job postings

Examples of technologies, by emergence year

| Emergence Year | Technology |
|---|---|
| 1934 | Radio transmitter |
| 1941 | Audio amplifier |
| 1946 | Lateral flow test |
| 1951 | Pulse generator |
| 1955 | Injection moulding |
| 1960 | MOSFET |
| 1962 | Printed circuit board |
| 1967 | Optical fiber |
| 1974 | Analog-to-digital converter |
| 1979 | Digital image processing |
| 1982 | Barcode |
| 1984 | Personal computer |
| 1988 | Polymerase chain reaction |
| 1995 | Mobile phone |
| 1999 | Carbon nanotube |
| 2000 | Marker assisted selection |
| 2003 | Wi-fi |

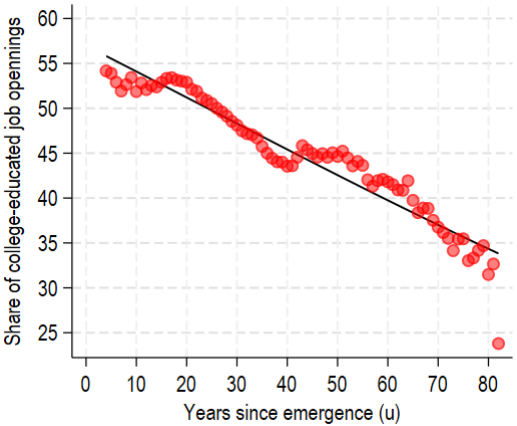
Total 6,259 technologies (1941 to 2006).

# Fact 1: Arrival of new technologies $m(b)$




- The pace was stable at 25–30 technologies per year before 1970, then peaked at 9X per year in the late 1980s.
- The surge in technology creation is robust across alternative measurement strategies.

# Fact 2: Share of college educated openings, by technology age




- Robust to cohort effects and ex. ICT.

**Model**:

$$\frac{h(u)}{l(u)} = \frac{\alpha(u)}{1-\alpha(u)} \left(\frac{w_H}{w_l}\right)^{-\gamma}$$

**Parametrize**:

$$\alpha(u) \;=\; \frac{exp(\theta_0 - \theta_1 u)}{1 + exp(\theta_0 - \theta_1 u)}.$$

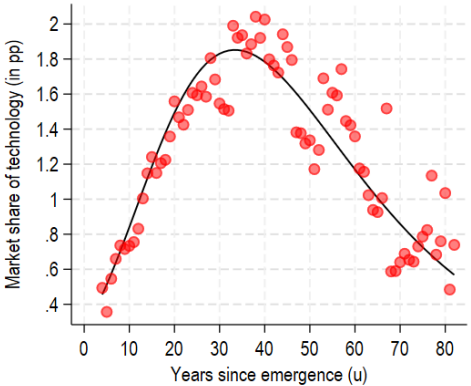
**Estimation equation**:

$$\ln\left(\frac{h(u)}{l(u)}\right) + \gamma \ln\left(\frac{W_h}{W_\ell}\right) = \theta_0 - \theta_1 u + \epsilon_u$$

- Substitute $\frac{h(u)}{l(u)} = \frac{\text{Share college postings (u)}}{\text{1-Share college postings(u)}}$
- assume $\gamma = 1.4$ (Katz and Murphy).

**Result**: $\theta_1 = 1.2\%$, $\theta_0 = 1.26$.

# Fact 3: Job postings life-cycle




- Tech employment peaks at 35 years after emergence.

**Model**:

$$\frac{h(u)+\ell(u)}{h+l} \propto z(u)^{\sigma-1}$$

**Parametrize**:

$$\dot{z}(u)/z(u) = g_m + (g_M - g_m)e^{-\lambda u}$$

**Estimate via NLLS**:

$$\frac{1}{\sigma-1}\ln\left(\frac{h(u)+\ell(u)}{h+l}\right)$$
$$= c + g_m u + \frac{1}{\lambda}(g_M - g_m)e^{-\lambda u} + ... + \varepsilon_u$$

– Assume $\sigma = 3.5$, $g = 2\%$.

**Results**: $g_M = 8.2\%$, $g_m = 0.2\%$ p.a., $\lambda = 0.048$

# Dimension 1: The Skill Premium over Time

# Results: Skill Premium over Time

- Given $\gamma = 1.4$, $\sigma = 3.5$, $g = 2\%$, and our estimates for $m(b)$, $\alpha(u)$, and $z(u)$.

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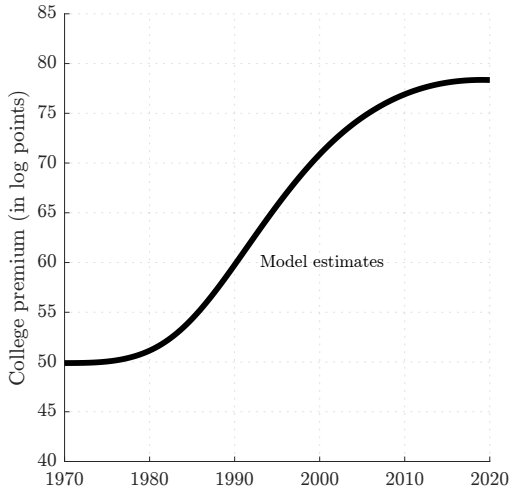
- Results:
  - 28 log-point (32%) increase in the college premium



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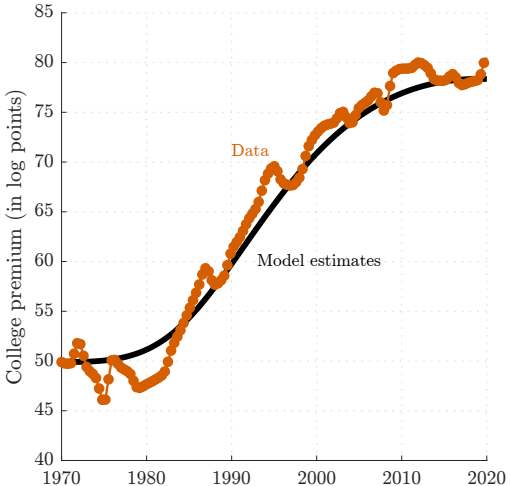

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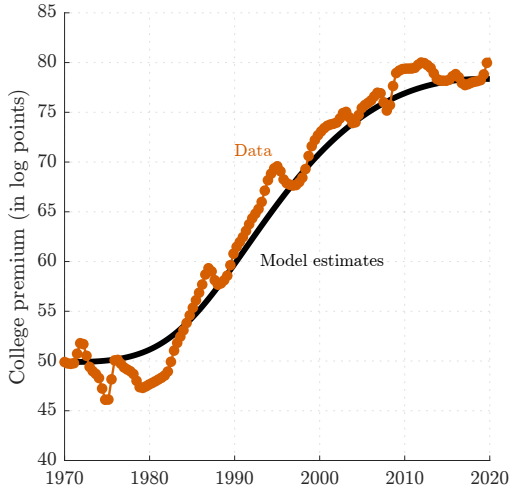
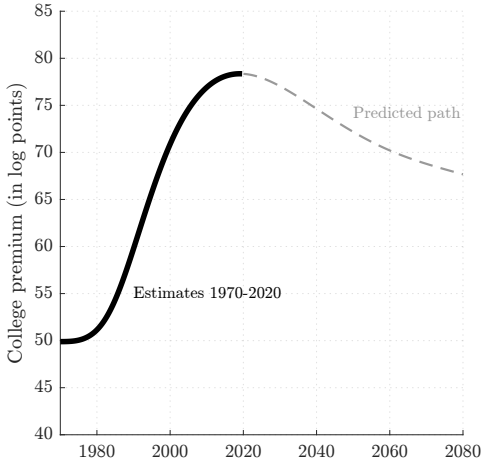
  - The mechanism explains one-third of the rise in relative demand for college workers.

Wages, output & TFP College supply

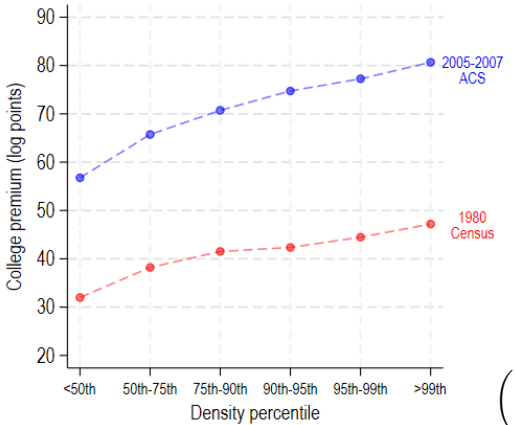


# The Future of Skill Premium



# Dimension 2: The Skill Premium across Space

# Explaining Differences Across Space: Model Extension with cities




**Facts to explain:**

1. College premium higher in dense areas
2. Gradient more pronounced in 2000s.

**Model extension:**

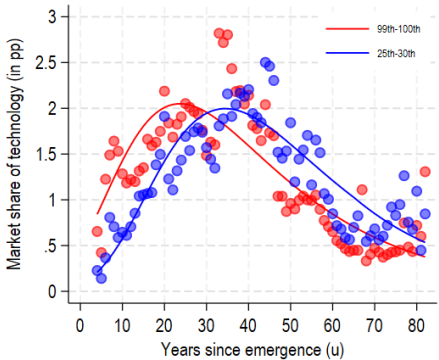
- Cities differ by density $d \in [0, 1]$
- **Key addition:** technology of age $u$ diffused to city $d$ with probability $p(d, u)$
- Skill premium under $\gamma = \sigma$:

$$\left( \frac{\int_0^\infty m_t(u)\, p(d,u)\, \alpha(u)\, e^{-(\sigma-1)gu}\, z(u)^{\sigma-1}\, du}{\int_0^\infty m_t(u)\, p(d,u)\, (1-\alpha(u))\, e^{-(\sigma-1)gu}\, z(u)^{\sigma-1}\, du} \right)^{1/\sigma} \left( \frac{h}{\ell} \right)^{-1/\sigma}$$

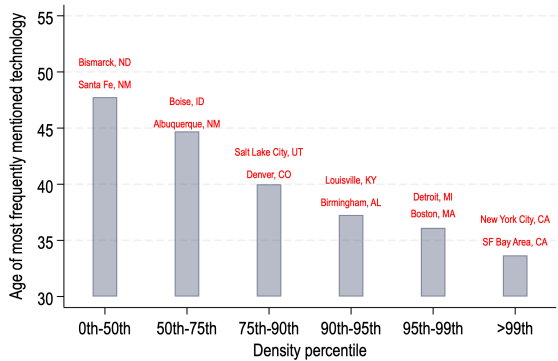
# Dense Places Use Younger Technologies

Our explanation: New techs introduced first in large cities, then diffuse across space.

**Market shares by density**



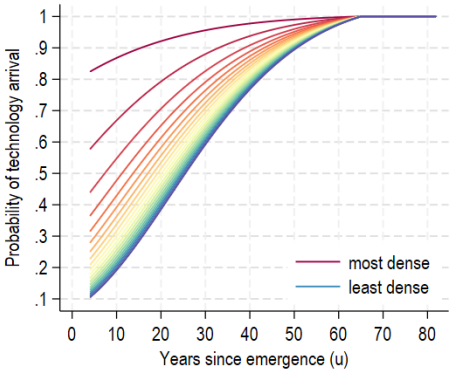

**Age of most frequently mentioned technology**



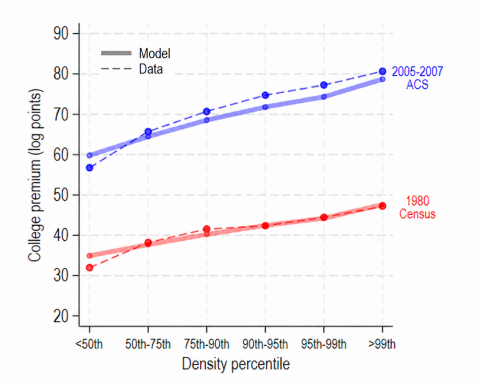

Regional technology life cycle

# Results - College premium by density

- Estimate $p(d, u)$ on market shares of technology age x city density, same method as before.



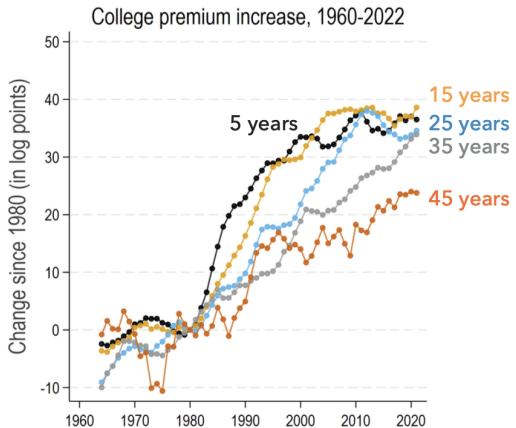

**Fitted diffusion probability $p(d, u)$**




**Skill premium (model vs data)**

# Dimension 3: The Skill premium across Cohorts

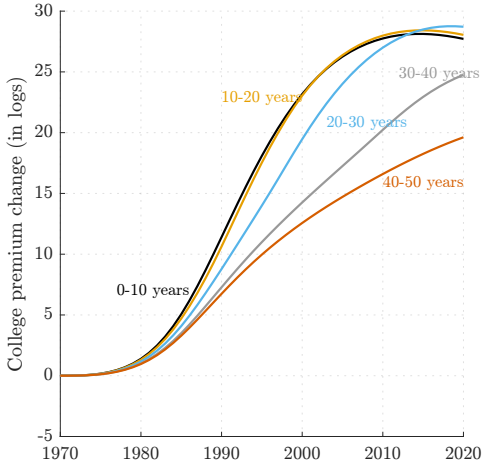
# Cohort Effects in College Premium




- **Card-Lemieux:** college premium rose first for young workers entering labor market.
- **Our Explanation:** young cohorts have a comparative advantage learning new technologies.
- **Addition to the model**: Workers of age $u_p$ have $a(u, u_p)$ efficiency units of labor in techs of age $u$ (plus experience terms).
- **Estimate**: $a(u, u_p)$ to match relative computer use at work by age (CPS) .

# The model explains 53% of the age gap in college-premium

*Changes in Skill Premia since 1970 in the model*



# Conclusion

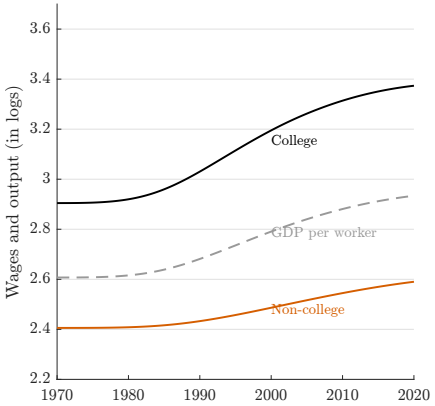
- The invention of new technologies and their diffusion in the labor market offer a compelling explanation for the dynamics of wage inequality.
- Our model is disciplined using data on **technology arrival and diffusion**:

1. A large number of innovations emerge between 1980 and 1995.
2. Technologies' labor market share peaks 35 years after their emergence.
3. The modal technology is 14 years younger in the top 1% densest locations than in the bottom 50% lowest-density locations.

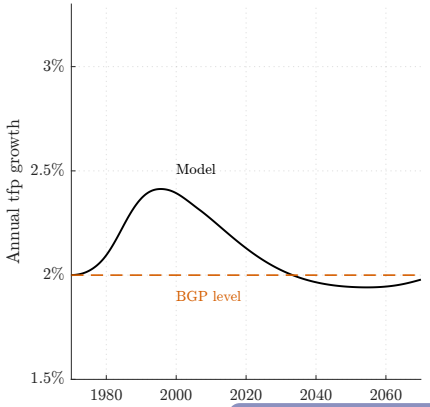
- Can rationalize variation in skill premium over time, across space and age groups.

# Additional result: Wages, output, and TFP

*Wages and output levels*



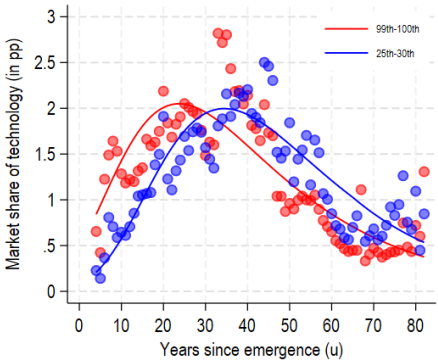

*TFP growth*



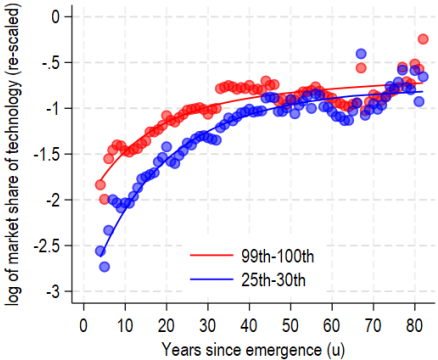

Back to skill-premium results

# Regional technology life cycle

*Employment share per technology*

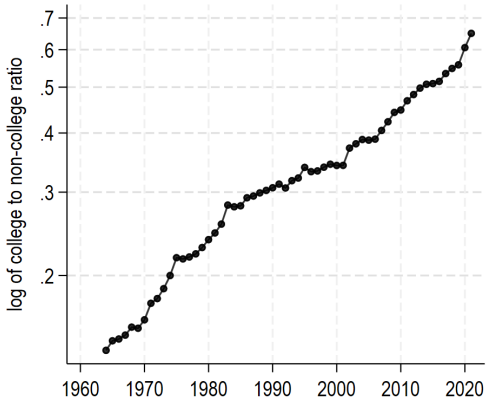



*Re-scaled employment share*




Back to spatial evidence

# Relative supply of college-educated workers




Ratio of hours worked by college-educated workers to non-college-educated workers, 1965–2021 (CPS; logarithmic scale).

Back to skill-premium results

# Skill broadening by regional density

| | Pooled OLS | Density FE | High density | Lower density | Heterogeneous slope |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| Age coefficient, -$\theta$_1 | –0.013*** | –0.013*** | –0.013*** | –0.013*** | –0.013*** |
| | (0.000) | (0.000) | (0.001) | (0.000) | (0.001) |
| Age coefficient, -$\theta$_1 · (Density $<$ 95 pct.) | | | | | 0.000 |
| | | | | | (0.001) |
| Constant term $\theta$_0 · (Density $<$ 95 pct.) | | | | | –0.032 |
| | | | | | (0.030) |
| Constant term $\theta$_0 | 1.057*** | 1.123*** | 1.111*** | 1.054*** | 1.086*** |
| | (0.011) | (0.008) | (0.021) | (0.012) | (0.027) |
| R-squared | 0.249 | 0.553 | 0.261 | 0.453 | 0.323 |
| N | 6,438 | 5,541 | 3,668 | 3,694 | 6,438 |

The decline in skill intensity with technology age is similar across high- and lower-density regions.

Back to spatial measurement

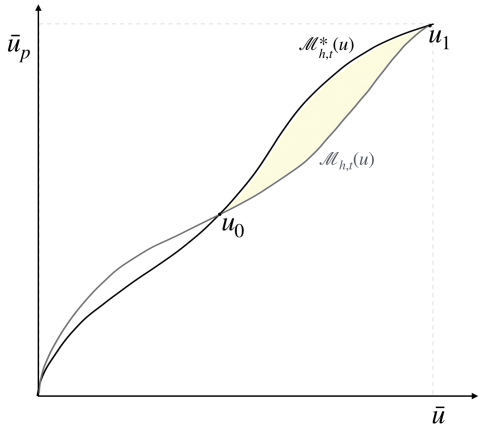
# Decomposition robustness across values of $\gamma$

| | Observed change (log points) (1) | Inferred shift in relative demand (2) | Contribution from changes in pace of technology (3) | Share explained by changes in the pace of technology (4) |
|---|---|---|---|---|
| *Value for* $\gamma$ : | | | | |
| 1.2 | 29.2 | -71.0 | 34.4 | 34.4% |
| 1.4 | 29.2 | -68.4 | 31.5 | 32.3% |
| 1.6 | 29.2 | -65.7 | 28.6 | 30.1% |
| 1.8 | 29.2 | -62.9 | 25.6 | 27.8% |
| 2.0 | 29.2 | -60.1 | 22.6 | 25.3% |

Changes in the pace of technology creation explain 25.3–34.4% of the inferred demand shift across the reported calibrations.

Back to decomposition

# Matching workers to technology vintages




Matching functions for skilled workers along the balanced growth path and a potential transition shift.

Back to cohort evidence

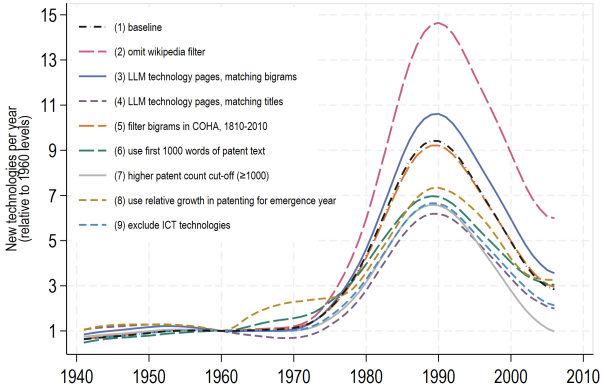
# Skill broadening - variation in specifications

Table: **Estimates of $\alpha(u)$ and robustness checks.**

| | | | | | Estimates at the cohort × year | | |
|---|---|---|---|---|---|---|---|
| | Baseline estimates, | Removing ICT | 2010 – 2015 | 2016 – 2023 | Panel | Time FEs | Cohort effects |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| Age coefficient, -$\theta$_1 | –0.012*** | –0.011*** | –0.010*** | –0.012*** | –0.013*** | –0.012*** | –0.022*** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.002) |
| Constant term $\theta$_0 | 1.260*** | 1.193*** | 1.280*** | 1.227*** | 1.315*** | 1.264*** | 1.328*** |
| | (0.020) | (0.024) | (0.029) | (0.026) | (0.022) | (0.021) | (0.024) |
| R-squared | 0.908 | 0.862 | 0.790 | 0.898 | 0.610 | 0.641 | 0.654 |
| N | 79 | 79 | 71 | 73 | 924 | 924 | 924 |

Back

# Fact 1: Arrival of new technologies $m(b)$ - robustness




- The surge in technology creation is robust across alternative measurement strategies.

# $z(u)$ estimates - variation in specifications

Table: **Estimates of $z(u)$ and robustness checks.**

| | | | | | Estimates at the cohort × year | | |
|---|---|---|---|---|---|---|---|
| | Baseline estimates | w/o ICT | 2010 – 2015 | 2016 – 2023 | Panel | Time FE | Cohort FE |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| $g_m$ | 0.002 | –0.018 | –0.007 | 0.001 | –0.006 | –0.015 | 0.003 |
| | (0.003) | (0.025) | (0.009) | (0.004) | (0.010) | (0.016) | (0.008) |
| $g_M$ | 0.082*** | 0.057*** | 0.080*** | 0.119*** | 0.089*** | 0.074*** | 0.069* |
| | (0.010) | (0.007) | (0.015) | (0.035) | (0.025) | (0.019) | (0.036) |
| $\lambda$ | 0.048*** | 0.016 | 0.041** | 0.055*** | 0.046** | 0.033* | 0.066 |
| | (0.009) | (0.010) | (0.016) | (0.015) | (0.021) | (0.018) | (0.045) |
| R-squared | 0.972 | 0.976 | 0.853 | 0.924 | 0.405 | 0.423 | 0.420 |
| N | 79 | 79 | 71 | 73 | 924 | 924 | 924 |

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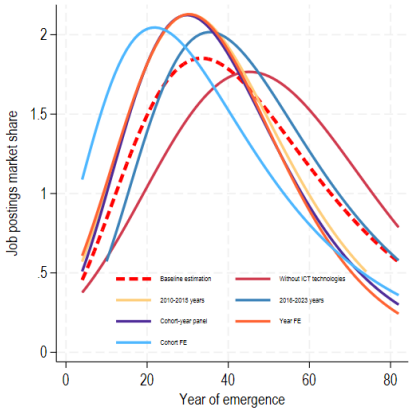
# Robustness: implied employment shares by technology age

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# Robustness of regional estimates

Table: **Joint estimates of $z(u)$ and $p(u,d)$ plus robustness checks.**

| | | | | | | Panel estimates at the density bin × cohort × year | | |
|---|---|---|---|---|---|---|---|---|
| | Baseline | $\bar{u} = 75$ | w/o ICT | 2010 – 2015 | 2016 – 2023 | Panel | Time FE | Cohort FE |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| *Estimates for $z(u)$:* | | | | | | | | |
| $g_m$ | 0.002* | 0.002 | 0.006*** | –0.002 | 0.002 | –0.002 | –0.004 | 0.006** |
| | (0.001) | (0.002) | (0.002) | (0.002) | (0.001) | (0.003) | (0.003) | (0.003) |
| $g_M$ | 0.081*** | 0.087*** | 0.063*** | 0.096*** | 0.184*** | 0.089*** | 0.082*** | 0.105** |
| | (0.018) | (0.015) | (0.011) | (0.020) | (0.056) | (0.023) | (0.019) | (0.045) |
| $\lambda$ | 0.073*** | 0.073*** | 0.044*** | 0.078*** | 0.093*** | 0.069*** | 0.061*** | 0.136*** |
| | (0.012) | (0.010) | (0.010) | (0.014) | (0.016) | (0.015) | (0.013) | (0.047) |
| *Estimates for $p(d,u)$:* | | | | | | | | |
| $\phi_0$ | 2.859*** | 2.695*** | 1.920*** | 2.658*** | 3.257*** | 2.754*** | 2.653*** | 2.549*** |
| | (0.409) | (0.320) | (0.308) | (0.464) | (0.908) | (0.538) | (0.488) | (0.444) |
| $\phi_1$ | 0.403*** | 0.422*** | 0.334** | 0.332** | 0.331** | 0.437** | 0.434** | 0.548*** |
| | (0.119) | (0.117) | (0.130) | (0.137) | (0.143) | (0.195) | (0.190) | (0.209) |
| $\phi_2$ | 0.035*** | 0.026*** | 0.032*** | 0.029** | 0.040** | 0.035** | 0.030* | 0.028* |
| | (0.011) | (0.009) | (0.012) | (0.013) | (0.016) | (0.018) | (0.015) | (0.016) |
| R-squared | 0.905 | 0.906 | 0.965 | 0.794 | 0.868 | 0.338 | 0.352 | 0.355 |
| N | 1,659 | 1,659 | 1,659 | 1,490 | 1,533 | 19,106 | 19,106 | 19,106 |

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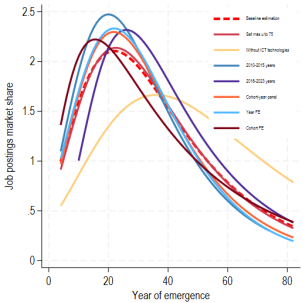
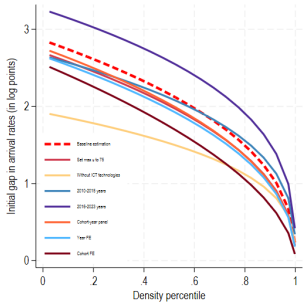
# Robustness: diffusion across space

*Panel A: Employment shares in highest-density locations*




*Panel B: Arrival gap across locations (log points)*

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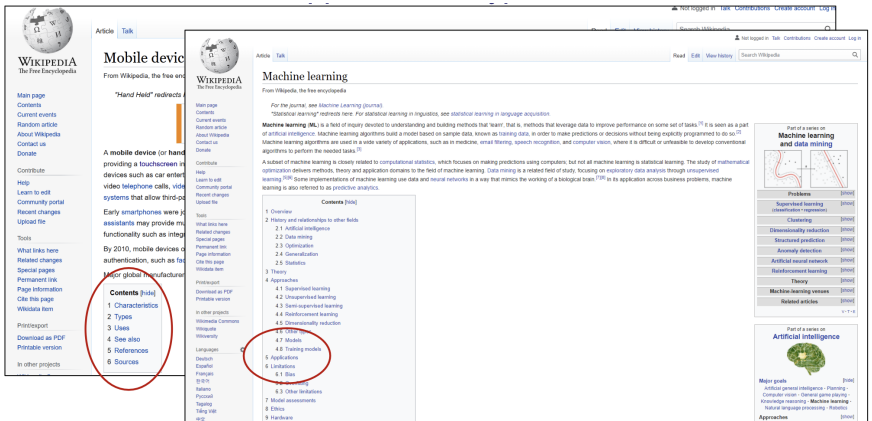
# Wikipedia technology page

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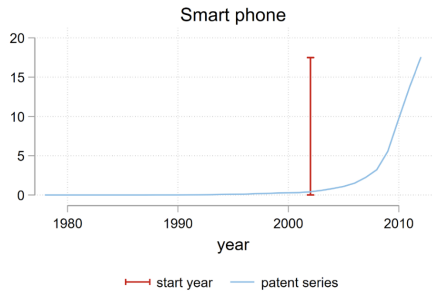
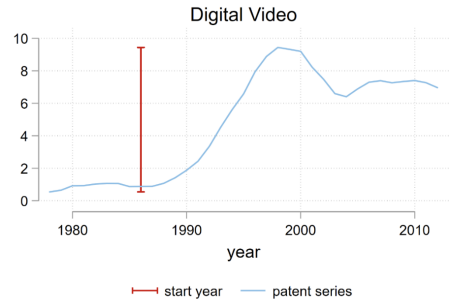
# Emergence year example

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# Job postings example

## Example job mentioning Machine Learning/AI

**1.0.1 JobTitle**

Applied Research Scientist, Video Understanding

**1.0.2 JobDomain**

www.glassdoor.co.in

**1.0.3 Standardized City**

New York

**1.0.4 JobText**

*Facebooks* mission is to give people the power to build community and bring the world closer together. Through our family of apps and services, were building a different kind of company that connects billions of people around the world, gives them ways to share what matters most to them, and helps bring people closer together. Whether were creating new products or helping a small business expand its reach, people at Facebook are builders at heart. Our global teams are constantly iterating, solving problems, and working together to empower people around the world to build community and connect in meaningful ways. Together, we can help people build stronger communities were just getting started.

Every day, massive amounts of video are uploaded into Facebooks services. In order to serve our communities better, it is critical that we can understand this content think about being able to answer questions like This person will like this video because.... or This person will find this video inappropriate because... Our goals broadly encompass content understanding, including the ability to produce video summaries, categorize content according to topic and purpose, identify audio events, find keyframes, and do keyword spotting. To achieve these goals, we are building a Video Understanding team in New York City, that will engage in a multidisciplinary effort combining —**SPEECH RECOGNITION, NATURAL LANGUAGE PROCESSING, and IMAGE PROCESSING**—. We view video as inherently multimodal content, and seek to develop methods that use all the information available. We are looking for researchers in — **MACHINE LEARNING** — and —**AI**— with strong software engineering skills, and a desire to build systems that will ship to billions of people. The Video Understanding Team is part of the Applied — **MACHINE LEARNING** — organization. The team carries out applied research in MLAI and designs, develops and deploys state of the art MLAI algorithms to the rest of Facebook. Our algorithms are used for ranking, improving content integrity, keeping communities safe, and power multiple product experiences across Facebook, Messenger, Instagram, WhatsApp and Oculus.

Responsibilities:

Develop highly scalable algorithms based on stateoftheart —**MACHINE LEARNING**— and neural network methodologies Conduct research to advance the stateoftheart, and publish work in relevant speech, NLP, and —**MACHINE LEARNING**— conferences and journals Apply expert coding skills to projects in partnership with other engineers across research, product, and infrastructure teams Adapt —**MACHINE LEARNING**— and neural network algorithms for training competitive, stateoftheart models which make the best use of modern parallel environments e.g. distributed clusters, GPU Minimum Qualifications:

MS degree in Computer Science or related quantitative field with 5 years of work experience, or Ph.D. degree in Computer Science or related quantitative field Knowledge of **MACHINE LEARNING, neural networks, and deep learning** Experience building systems based on —**MACHINE LEARNING**— andor **DEEP LEARNING** methods, especially in the areas of —**SPEECH RECOGNITION, NATURAL LANGUAGE PROCESSING, and IMAGE PROCESSING**—, or other machineperception tasks Experience developing and debugging in CC andor Python

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