

Skill premium in times of Rapid Technological Change

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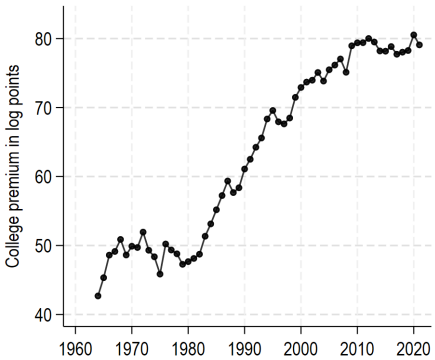
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Views are our own, not of the STL Fed/Fed System.

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:

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

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- **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 (Kalyani et. al., 2025, QJE)

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)

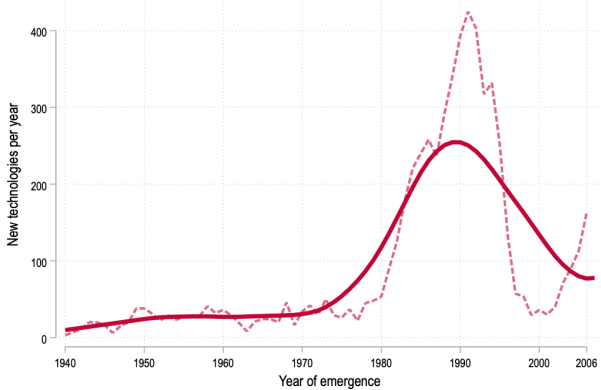
Wikipedia | Patent examples | Job postings

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

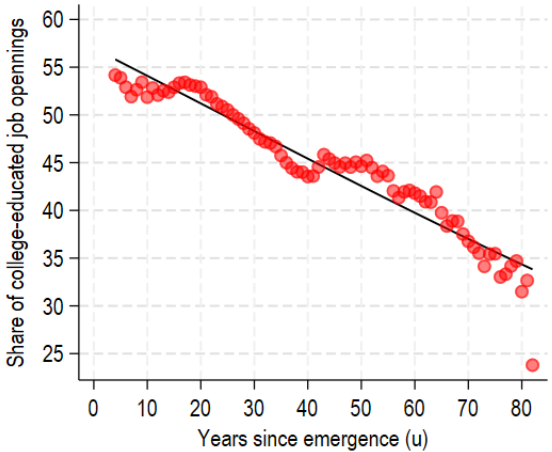
Total 6,259 technologies (1941 to 2006).

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



- The pace was stable at 25–30 technologies per year before 1970, then peaked at 250 per year in the late 1980s.
- It subsequently declined to about 100 technologies per year during 2000–2007.
- The surge in technology creation is robust across alternative measurement strategies.

Fact 2: Skill bias and broadening (Kalyani et. al., 2025, QJE)



- For newly introduced technologies, 57% of job postings require a college degree.
- The share falls to 34% for technologies that are 80 years old.
- The pattern is robust to cohort effects and trends in Lightcast data.
- Similar estimates without ICT.

Fact 2: Estimating $\alpha(u)$ using skill broadening

Model:

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

Parametrize:

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

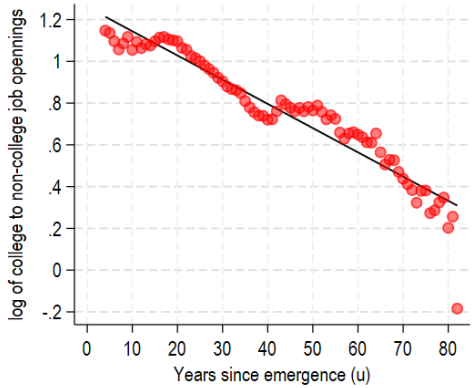
Estimation equation:

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

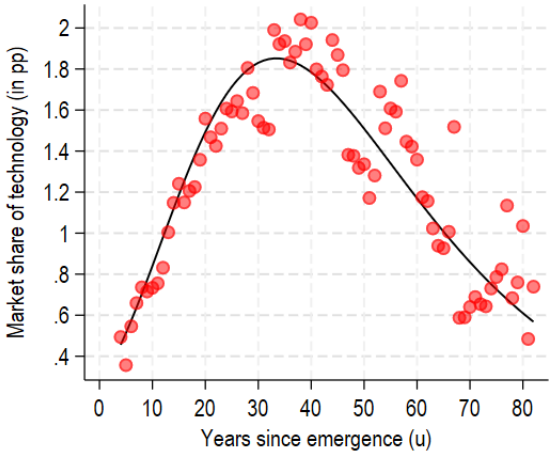
Assume $\gamma = 1.4$ (Katz and Murphy).

Results:

- $\theta_1 = 1.2\%$ (s.e. $= 0.1\%$).
- $\theta_0 = 1.26$ (s.e. $= 0.020$).



Fact 3: Job postings life-cycle



- Employment shares peak about 35 years after a technology emerges.

Robustness

Fact 3: Estimating $z(u)$ - Productivity Growth of Technologies

Model:

- Job market share in the model:

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

- Parametrize productivity growth:

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

- Estimate via NLLS:

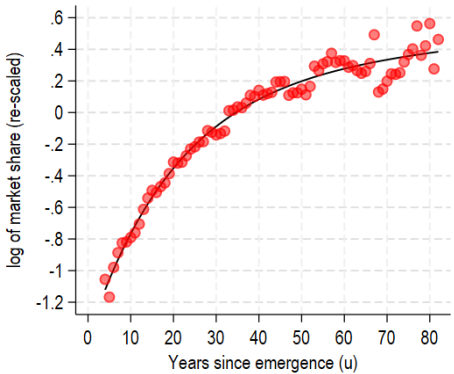
$$\frac{1}{\sigma-1}\ln\left(\frac{h(u)+\ell(u)}{h+l}\right) + \ln(f(\cdot))$$
$$= c + g_m u + \frac{1}{\lambda}(g_M - g_m)e^{-\lambda u} + \varepsilon_u$$

- Assume $\sigma = 3.5$, $g = 2\%$.

Results:

Details

- $g_M = 8.2\%$ p.a. (s.e. $= 1.0\%$)
- $g_m = 0.2\%$ (s.e. $= 0.3\%$)
- $\lambda = 0.048$ (s.e. $= 0.009$)



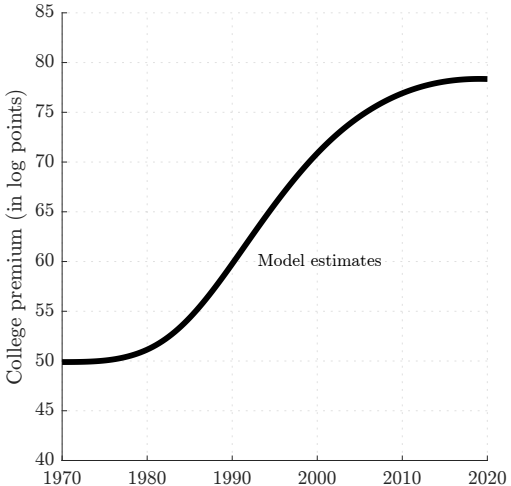
Dimension 1: The Skill Premium over Time

Results: Skill Premium over Time

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

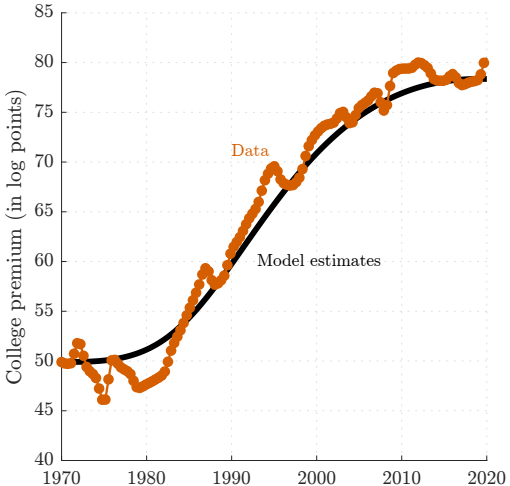
Results: Skill Premium over Time

- Given $\gamma = 1.4$, $\sigma = 3.5$, $g = 2\%$, and our estimates for $m(b)$, $\alpha(u)$, and $z(u)$.
- Results:
  - 28 log-point (32%) increase in the college premium



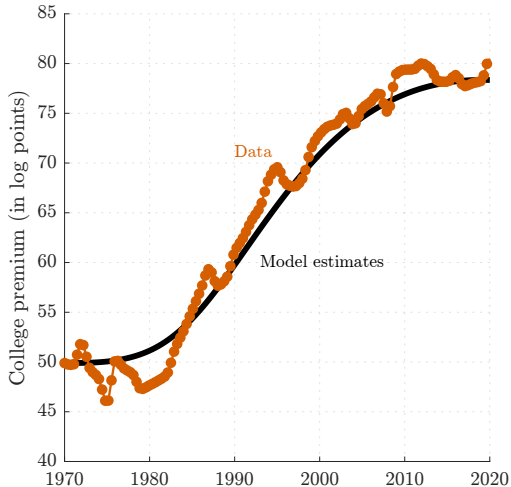
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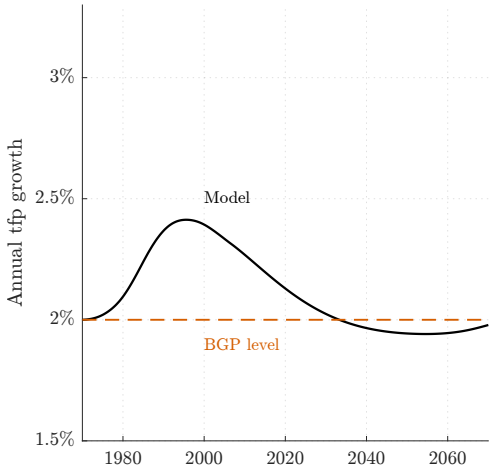
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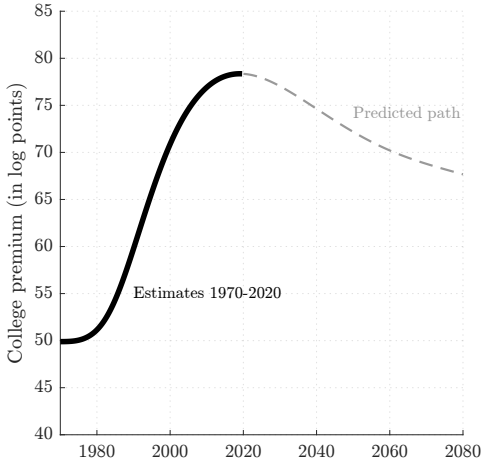
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  - 28 log-point (32%) increase in the college premium
  - The mechanism explains one-third of the rise in relative demand for college workers.
  - TFP growth peaks at 2.4% p.a. in 1995 and then productivity slowdown

Wages, output & TFP | College supply

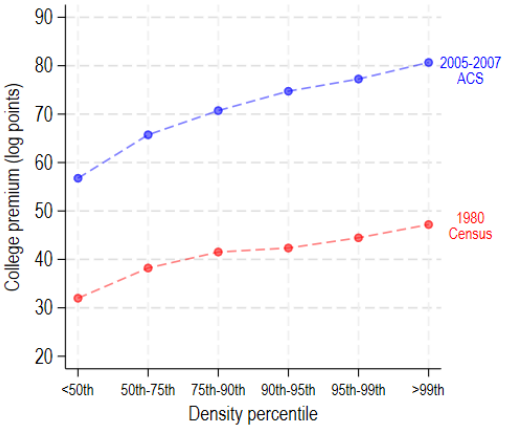


The Future of Wage Inequality



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.

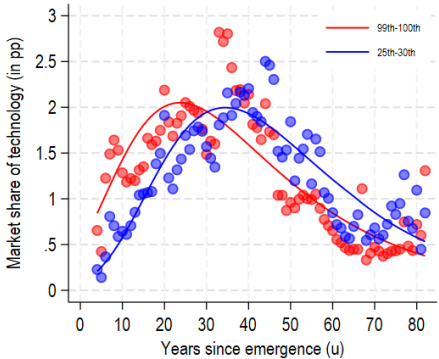
Model extension:

- Cities differ by density $d \in [0, 1]$
- **Key addition:** technology of age u diffused to city d with probability $p(d, u)$
- $p(d, u)$ enters aggregation and labor market clearing:

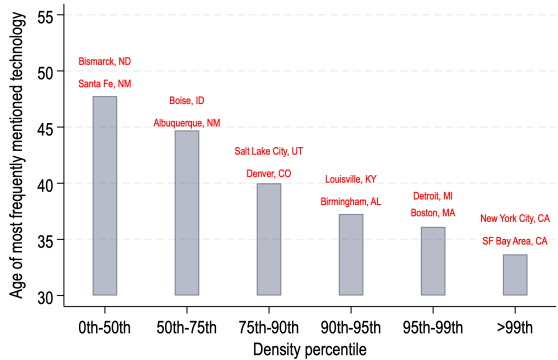
$$Y_t(d) = \left(\int_0^\infty m_t(u)\, p(d,u)\, y_t(d,u)^{\frac{\sigma-1}{\sigma}}\, du \right)^{\sigma/(\sigma-1)}$$

Dense Places Use Younger Technologies

Market shares by density



Age of most frequently mentioned technology



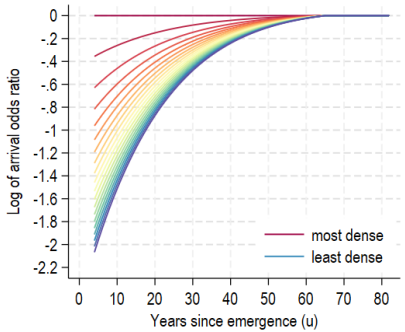
Our explanation: new technologies introduced first in large cities and diffuse across space over time.

Regional technology life cycle

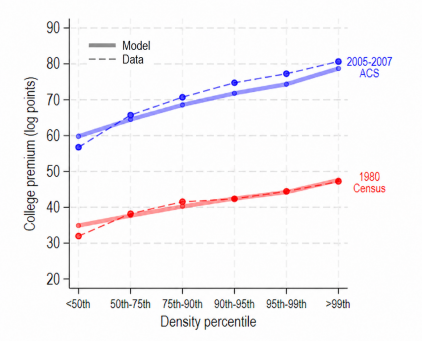
Results - College premium by density

Estimate $p(d,u)$ using the same methodology as before, and calculate skill premium for city (d):

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



Fitted diffusion probability $p(d,u)$

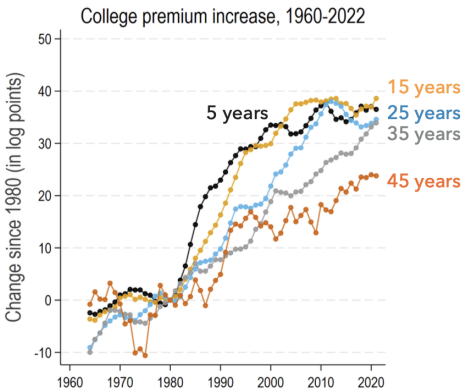


Skill premium (model vs data)

Dimension 3: The Skill premium across Cohorts

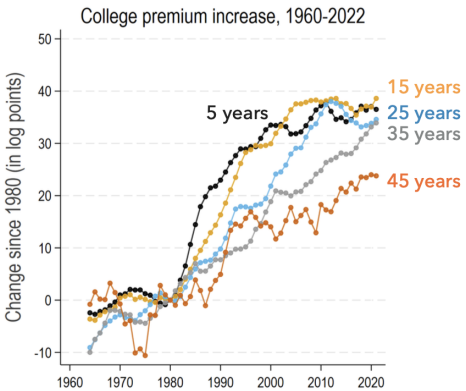
Cohort Effects in College Premium

- **Card-Lemieux:** college premium rose first for young workers entering labor market.

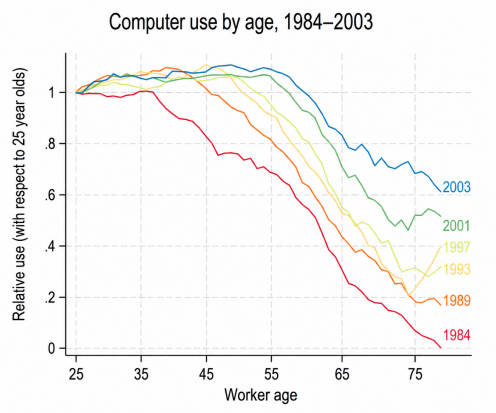


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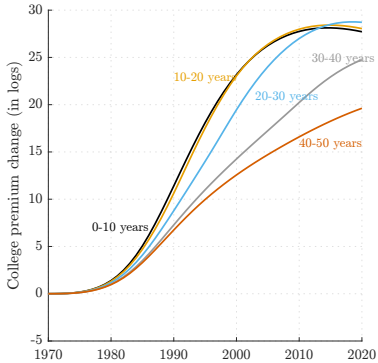
- **Our Explanation:** young cohorts have an advantage learning new technologies.



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

- Make one change 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).
- Discipline $a(u, u_p)$ to relative computer use at work by age.

Changes in Skill Premia since 1970



Conclusion

- The invention of new technologies and their application in the labor market offer a compelling explanation for the dynamics of wage inequality.
- Discipline with new data on technology emergence and diffusion in the labor market:

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 over time, across space and age groups.

Top technologies by year of emergence (1941–1957)

Title	Top bigram	Year
motor drive	drive_motor	1941
recording head	recording_head	1942
spring-loaded camming device	spring_loaded	1943
voltage divider	output_voltage	1944
adipic acid	adipic_acid	1945
corrosion inhibitor	corrosion_inhibitor	1946
dichloromethane	methylene_chloride	1947
programmable interval timer	output_signal	1948
chemical reaction	reaction_condition	1949
methacrylic acid	methacrylic_acid	1950
pulse generator	pulse_generator	1951
polymer solution	polymer_solution	1952
level shifter	voltage_level	1953
electrical element	circuit_element	1954
pull-up resistor	resistor_connected	1955
electrically conductive adhesive	electrically_conductive	1956
epoxy	epoxy_resin	1957

Back to data

Next: 1958–1974

Top technologies by year of emergence (1958–1974)

Title	Top bigram	Year
propylene glycol	propylene_glycol	1958
chain-growth polymerization	polymer_chain	1959
flowchart	flow_chart	1960
ac power plugs and sockets	ac_power	1961
pulse-width modulation	pulse_width	1962
antioxidant	free_radical	1963
laser beam machining	laser_beam	1964
duty cycle	duty_cycle	1965
phase-shift keying	phase_shift	1966
particle-size distribution	particle_size	1967
printed circuit board	printed_circuit	1968
methyl acetate	methyl_ester	1969
multiplexer	input_signal	1970
pressure measurement	pressure_sensor	1971
compacted oxide layer glaze	oxide_layer	1972
size-exclusion chromatography	pore_size	1973
graphics processing units	processing_unit	1974

Previous | Back to data | Next: 1975–1991

Top technologies by year of emergence (1975–1991)

Title	Top bigram	Year
tert-butyl alcohol	tert_butyl	1975
immortalised cell line	cell_line	1976
lateral flow test	reaction_zone	1977
growth factor	growth_factor	1978
nucleic acid	nucleic_acid	1979
targeted drug delivery	drug_delivery	1980
solar cell	solar_cell	1981
bovine serum albumin	bovine_serum	1982
operational data store	data_stored	1983
holographic optical element	optical_element	1984
personal computer	personal_computer	1985
communications system	communication_system	1986
user interface	user_interface	1987
polymerase chain reaction	chain_reaction	1988
polyethylene glycol	polyethylene_glycol	1989
universal remote	remote_control	1990
electrical connector	electrically_connected	1991

Previous | Back to data | Next: 1992–2006

Top technologies by year of emergence (1992–2006)

Title	Top bigram	Year
internet protocol suite	internet_protocol	1992
cable & wireless communications	wireles_communication	1993
carboxymethyl cellulose	carboxymethyl_cellulose	1994
real-time polymerase chain reaction	pcr_product	1995
omega-3 acid ethyl esters	ethyl_ester	1996
sense strand	sense_strand	1997
mobile device	mobile_device	1998
carbon nanotube	carbon_nanotube	1999
marker-assisted selection	desired_trait	2000
snp array	polymorphism_snp	2001
silo	bulk_storage	2002
wi-fi 6	wi_fi	2003
coaxial cable	coaxial_cable	2004
linoleic acid	linoleic_acid	2005
tablet computers	tablet_computer	2006

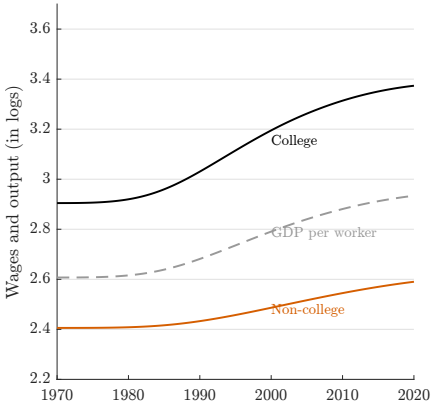
The technology with the most patent mentions in each emergence year, together with its most-mentioned bigram.

Previous

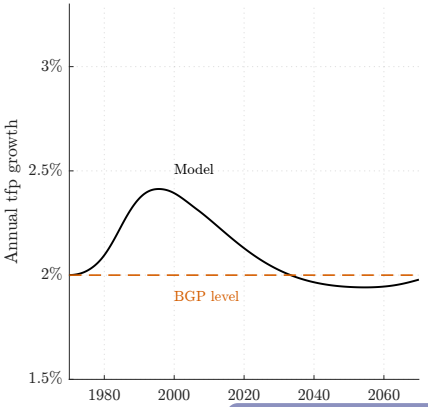
Back to data

Additional result: Wages, output, and TFP

Wages and output levels



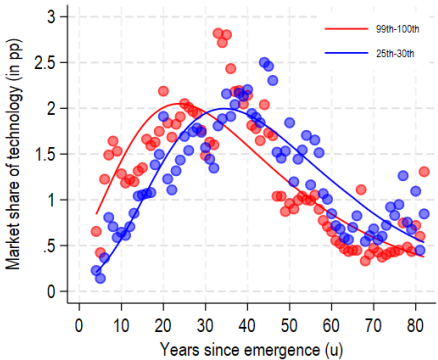
TFP growth



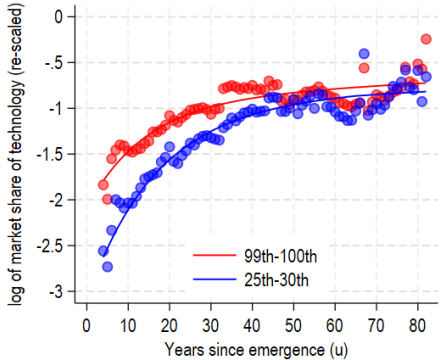
Back to skill-premium results

Regional technology life cycle

Employment share per technology

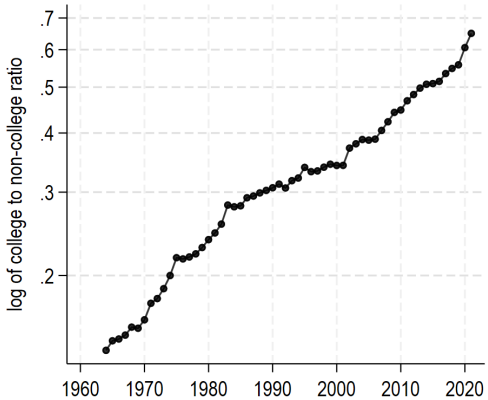


Re-scaled employment share



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, -θ_1	–0.013***	–0.013***	–0.013***	–0.013***	–0.013***
	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)
Age coefficient, -θ_1 · (Density $<$ 95 pct.)					0.000
					(0.001)
Constant term θ_0 · (Density $<$ 95 pct.)					–0.032
					(0.030)
Constant term θ_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

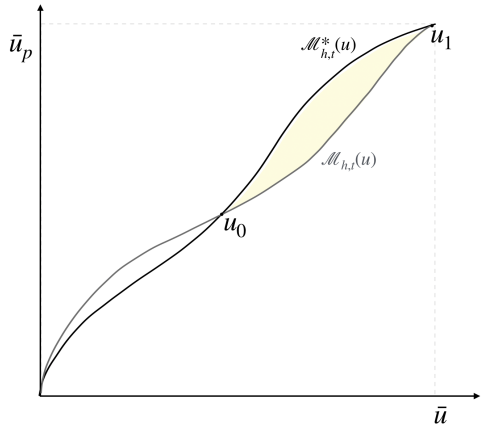
Decomposition robustness across values of γ

	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 γ :				
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, -θ_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 θ_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

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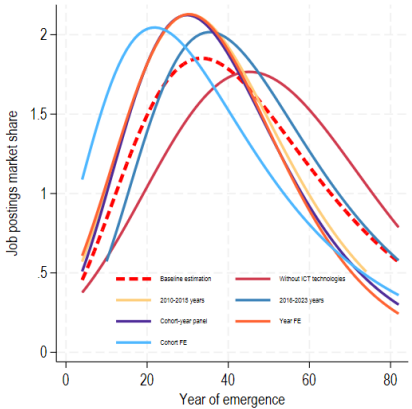
$z(u)$ estimates - variation in specifications

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)
λ	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

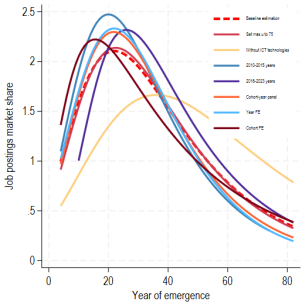
Table: **Joint estimates of $z(u)$ and $p(u,d)$ plus robustness checks.**

						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)
λ	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 $p(d,u)$:								
ϕ_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)
ϕ_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)
ϕ_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

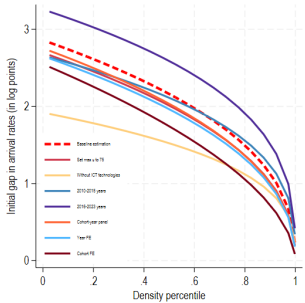
Back to spatial measurement

Robustness: diffusion across space

Panel A: Employment shares in highest-density locations

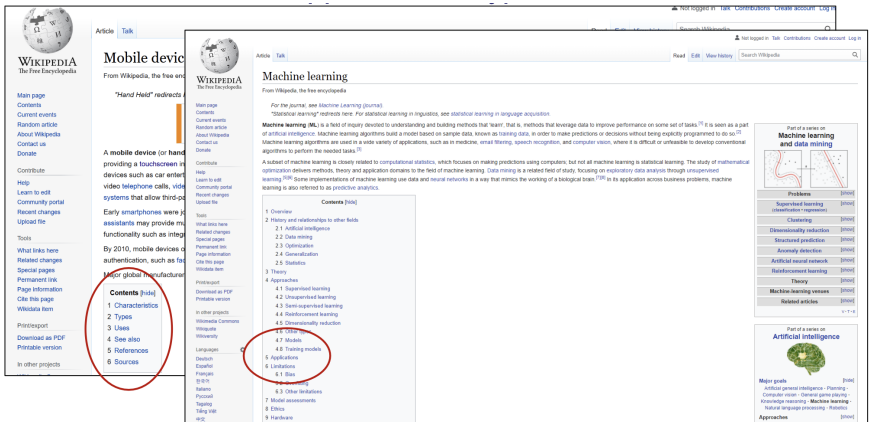


Panel B: Arrival gap across locations (log points)



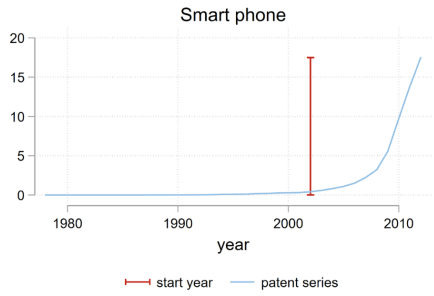
Back to spatial measurement

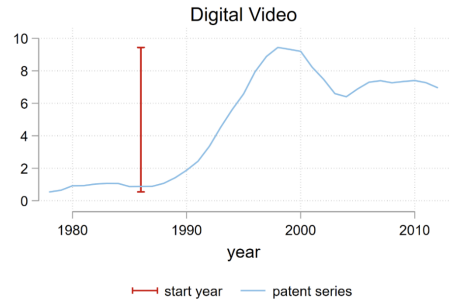
Wikipedia technology page



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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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