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Degrees for GPTs: The Effects of Generative AI on Skill Demand and Supply

Samuel Dodini[1] Tucker Smith[1] Yaling Xu[2]

[1]Federal Reserve Bank of Dallas

[2]Norwegian School of Economics

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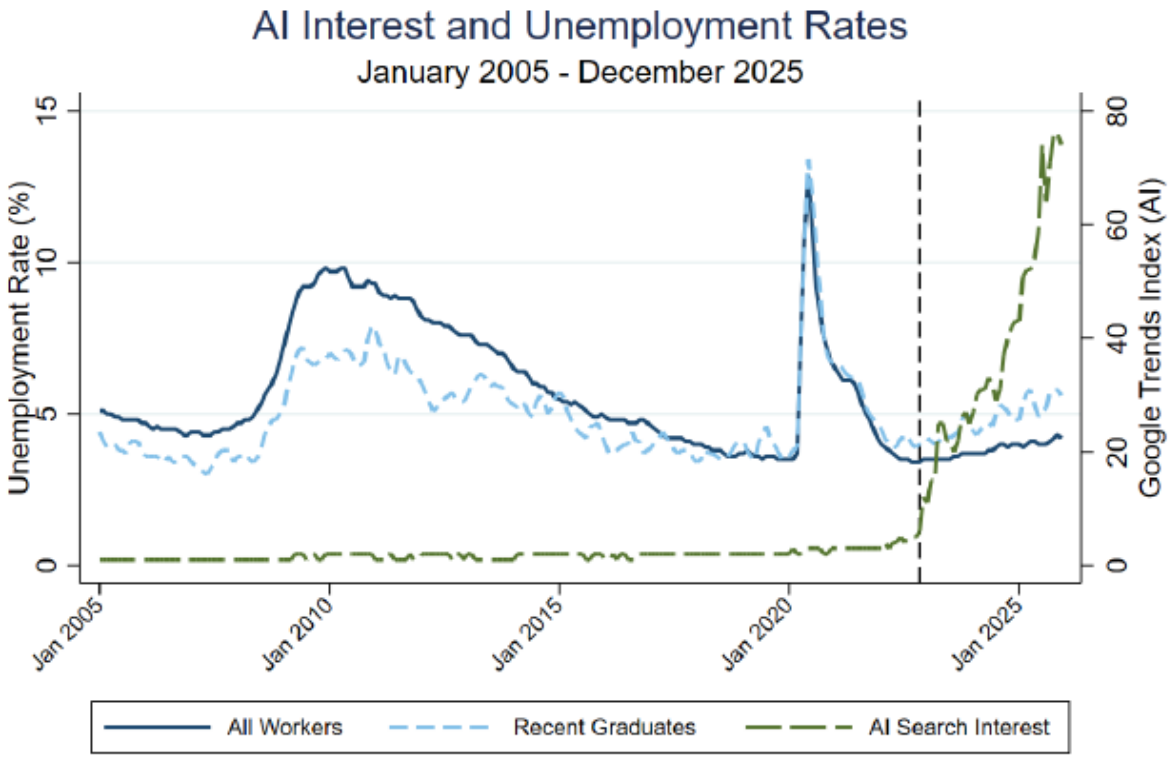
Disclaimer

The views expressed in this paper are those of the authors and do not necessarily reflect those of the Federal Reserve Bank of Dallas or the Federal Reserve System.

The conclusions of this research do not necessarily reflect the opinion or official position of the University of Houston Education Research Center, the Texas Education Agency, the Texas Higher Education Coordinating Board, the Texas Workforce Commission, or the State of Texas.

Generative AI and the Demand for Skills



Seasonally adjusted 3-month moving averages, NY Fed (CPS). Recent graduates: ages 22–27.

Who bears the cost of the transition, and how do they adjust?

Why Focus on Young Adults?

- Coincident timing of GenAI diffusion and unusually large increases in unemployment for young college graduates
- Early evidence: GenAI *substitutes* for less-experienced labor, *complements* experience (Brynjolfsson et al., 2025; Hosseini and Lichtinger, 2025; Orr et al., 2026)
- Under uncertainty about AI's capabilities, reducing hiring is cheaper than layoffs
- Graduating into weak labor demand $\Rightarrow$ persistent earnings losses. (Kahn, 2010; Oreopoulos et al., 2012)
- Workers will need skills that complement the technology
  - Skill-development responses are hard to observe among entrenched workers – but visible among individuals attached to the formal education system

This Paper

Questions

- How did the GenAI shock to labor demand affect earnings and employment of new college graduates?
- How are graduates and current students adjusting their educational investments?
- Do adjustments appear likely to pay off?

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- Linked individual-level education and earnings records for all Texas public university students (UHERC)

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Research Design

- Project task-based AI exposure measures onto fields of study
- Continuous-dose event study: more- vs. less-exposed majors, cohorts after vs. before ChatGPT (Callaway et al., 2025)

Preview of Results

Did the GenAI demand shock reach new graduates?

- Job postings fell **5%** within a year of ChatGPT and ∼**10%** by mid-2026 for occupations with a 10 p.p. greater automatable task share
- First-year earnings fell by over **$3,000** (≈**10%**) for 2024 graduates from majors with a 10 p.p. greater automatable task share — driven *roughly equally* by employment (−2.8%) and conditional earnings (−5%), and persisting into the second year

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Did students adjust educational decisions?

- Graduate-school enrollment rose **0.9 p.p.** (**6%**), but graduates largely kept studying the *same* field
- Upperclassmen: enrollment and course-taking continued on trend
- New college entrants: enrollment fell **6%** more between Fall 2022 and Fall 2025 in majors with a 10 p.p. greater automatable task share

Preview of Results

Do adjustments appear likely to pay off?

- New master's recipients in exposed fields experienced similar (or even larger) declines in earnings as four-year graduates
- Graduates from more-exposed majors with greater course specialization experienced even larger earnings losses
- Suggests viability of "pivoting" responses over "upskilling"

Empirical Strategy

Data Sources

Lightcast: job postings

- Texas online job postings, occupation, industry, firm, experience requirements, and desired majors.
- Construct Occupation $\times$ industry $\times$ quarter panel & firm $\times$ quarter panel

University of Houston Education Research Center: linked individual-level education and earnings records

- **THECB**: SAT/ACT scores, course enrollment, declared majors, degrees, demographics (all TX public colleges)
- **TWC**: quarterly earnings, employment, and industry for all UI-covered TX workers
- Construct panels of bachelor's graduates, master's graduates, and first-time university entrants

Lightcast vs. JOLTS | Experience Requirements

Defining AI Exposure

Occupation level. Share of an occupation's tasks GenAI could perform more efficiently

- Eloundou et al. (2023): rubric-based "theoretical" exposure; O*NET tasks scored by annotators and GPT-4
- Handa et al. (2025) — share of an occupation's O*NET tasks that *Claude users actually automated* as of Fall 2024
- Observed use preferred: legal and verification constraints drive wedges from theoretical exposure (Bick et al., 2025; Massenkoff and McCrory, 2026), which itself varies sharply with the rating LLM (Yin et al., 2026)

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Field-of-study level. Students choose *fields of study*, not occupations directly

$$MajExp_m = \sum_o \omega_{mo} \times OccExp_o$$

- ω_{mo}: share of *pre-AI* job postings listing major m that were for occupation o; fields = 4-digit CIP codes

$\Rightarrow$ $MajExp_m \approx$ share of tasks in a graduate's pre-AI job set at risk of automation

Major Exposure Levels

Exposure Level	Example Fields of Study
$MajExp_m < 0.1$	Agricultural/Biological Engineering, Animal Sciences, Astronomy, Business Administration, Ecology, Economics, Elementary Education, History, Hospitality Administration, Human Development, Mental and Social Health Services, Mining and Mineral Engineering, Nutrition Sciences, Philosophy, Plant Sciences, Psychology, Real Estate, Registered Nursing, Urban Studies
$0.1 \leq MajExp_m < 0.2$	Engineering, Journalism, Mathematics, Political Science, Statistics
$MajExp_m \geq 0.2$	Computer Science, Computer Engineering, Geography and Cartography, Linguistic, Comparative, and Related Language Studies, Systems Science and Theory

Notes: Four-digit CIP codes. $MajExp_m$ is the average share of tasks among pre-AI job postings listing major m that can be automated, based on Claude usage reported by Anthropic.

Event-Study Specification

$$y_{imt} = \sum_{\substack{\tau \\ \tau \neq t^* - 1}} \pi_{\tau}^{ES} \mathbb{1}\{t = \tau\} \times MajExp_m + \alpha_m + \alpha_t + \Phi S_i + \epsilon_{imt}$$

- y_{imt}: outcome for individual i from major m, cohort t
- α_m: time-invariant differences across majors (economists always out-earn English majors)
- α_t: shocks common to all majors within a cohort (the pandemic)
- S_i: race, ethnicity, gender, college entrance exam score
- Standard errors clustered by major
- **"Strong"** parallel trends assumption (Callaway et al., 2025)

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- **"Strong"** parallel trends assumption (Callaway et al., 2025)
- $\hat{\pi}_{\tau}^{ES}$ = difference in outcomes associated with a **10 p.p. higher** automatable task share, relative to that difference in the reference cohort

Identification Concerns

Any time-varying shock correlated with $MajExp_m$ threatens π_τ^{ES}

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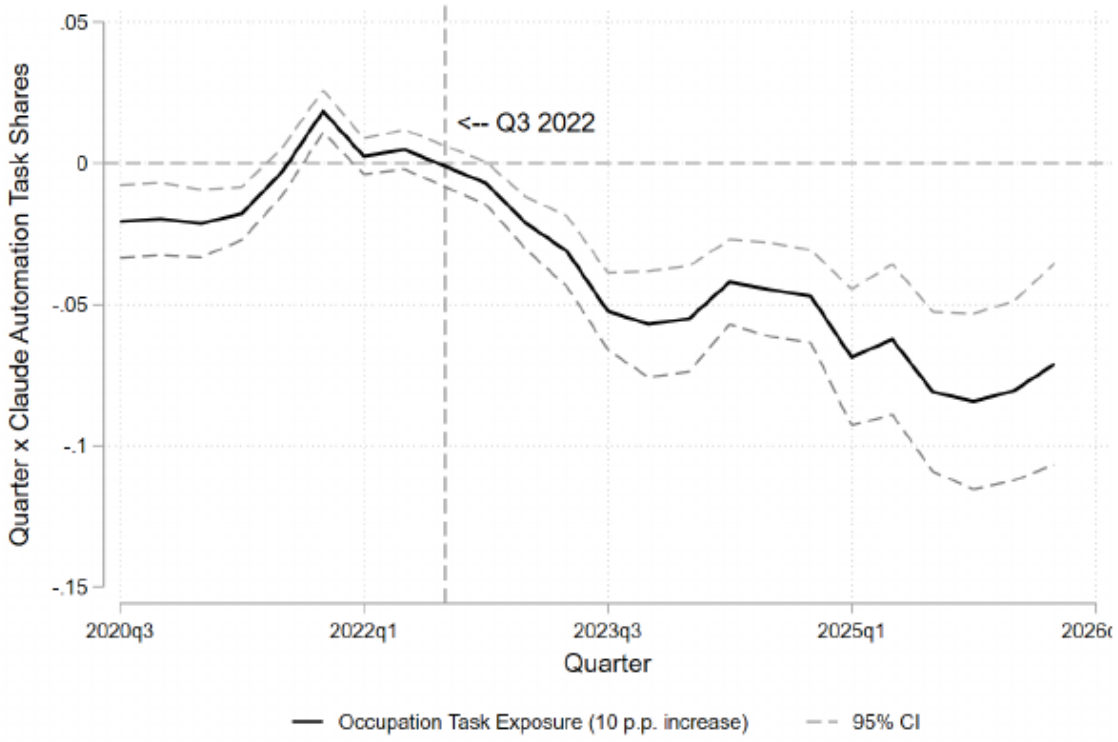
1. **Industry-specific shocks:** Tech boom-and-bust; differential bite of the 2022–23 rate hikes (Zens et al., 2020) Ind. × Year FEs
2. **Remote work:** WFH proliferation may independently reduce demand for young workers (Lambert and Schindler, 2026; Emanuel et al., 2026; Mask, 2026) Remote Controls
3. **School-wide shocks:** E.g. remote-learning policies at schools that produce more exposed graduates *(school-by-year FEs throughout)*
4. **Selection into majors:** Changing composition of students choosing exposed fields SAT Selection
5. **Migration/graduate school:** could mechanically depress observed earnings Drop Grad Enrollees
6. **"Other" AI causal stories:** learning loss; deterioration of signal value

Effects of GenAI on Job Openings & New Entrants

Postings Fell for More-Exposed Occupations

$$\log E(y_{okt} \mid \mathbf{x}_{okt}) = \alpha_{ok} + \alpha_{kt} + \sum_{\tau} \pi_{\tau}^{ES} \mathbb{1}\{t = \tau\} \times OccExp_o$$

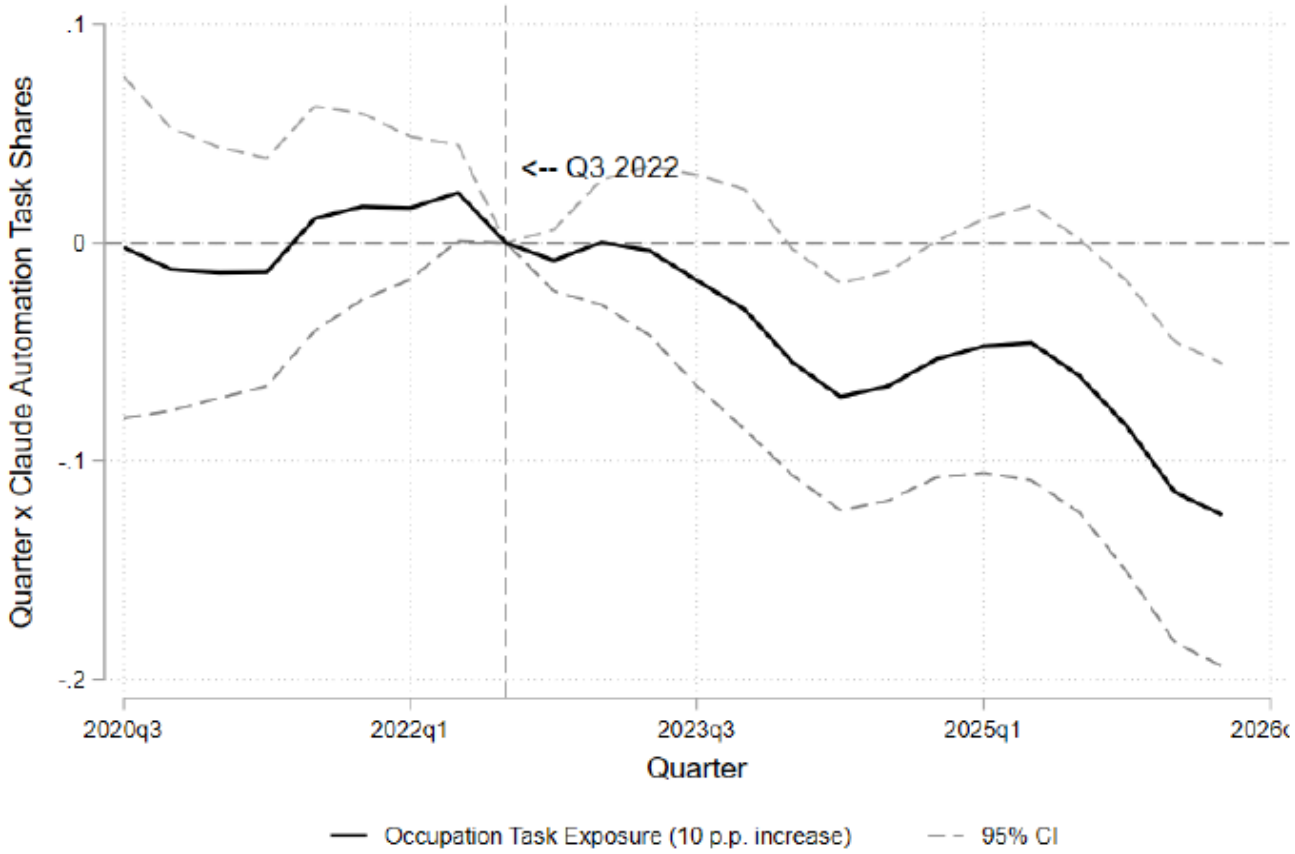


Quarterly ad counts by occupation-industry

↓ 5% within a year of ChatGPT; ↓∼10% through 2026:Q2

Spatial Controls | Monetary Policy & Remote Work

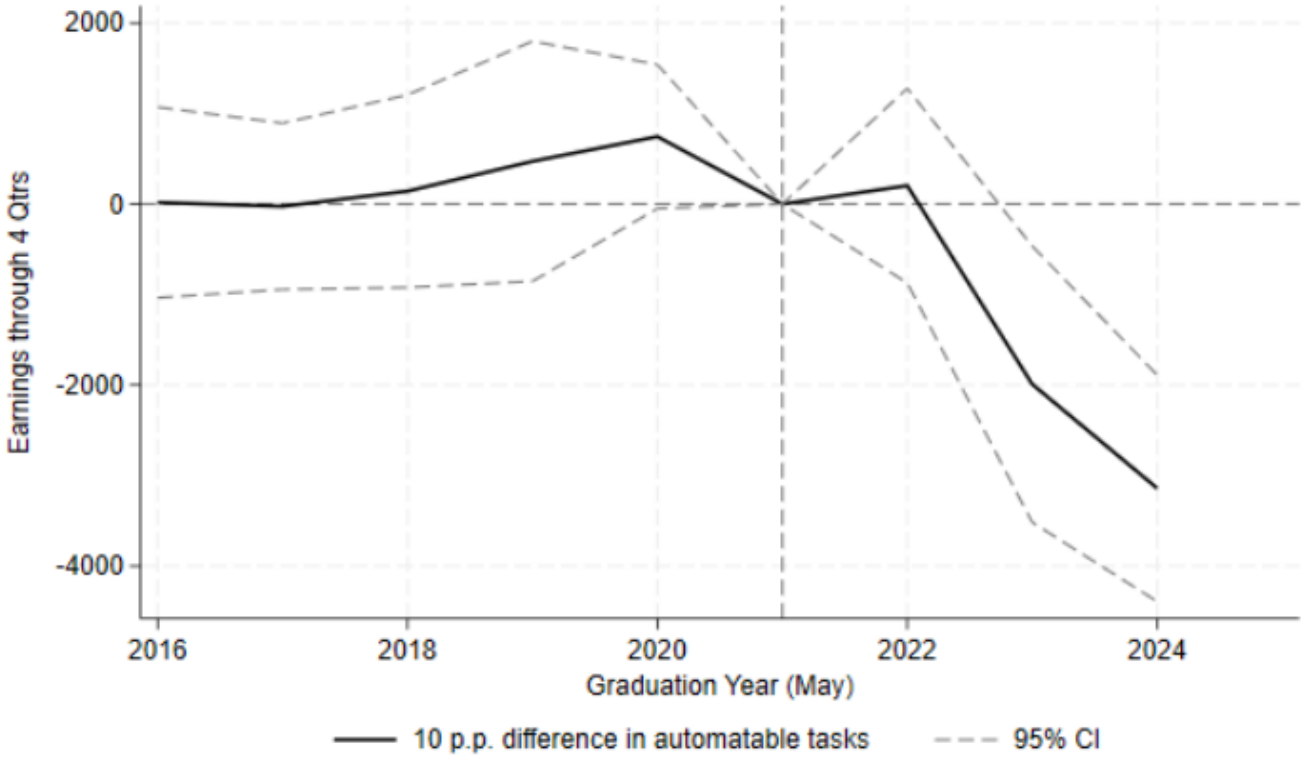
Incumbent Firms Posted Fewer Openings



Quarterly ad counts by firm, balanced panel

↓∼8% by early 2024 per 10 p.p. of baseline firm exposure

Earnings Fell for Graduates from AI-Exposed Majors



Total earnings, first four quarters after graduation (2025$, incl. zeroes)

2023: $\approx -\$2{,}000$ 2024: $\approx -\$3{,}000$ $\downarrow \sim 10\%$ of the pre-GenAI mean

Effects Persist into the Second Year

	(1) Earnings	(2) # of Qtrs Employed	(3) Earnings, Employed All 4 Qtrs
A. Qtrs 1–4 After Graduation			
$MajExp_m$	-2,012**	-0.083***	-934
	(776)	(0.020)	(622)
N	280,532	280,532	156,339
B. Qtrs 5–8 After Graduation			
$MajExp_m$	-2,351***	-0.045**	-2,102***
	(726)	(0.018)	(481)
N	280,532	280,532	133,365

Standard errors clustered by major in parentheses. May 2023 graduates, relative to May 2021.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Why might effects persist?

- Recession-entry scarring persists for a decade or more (Kahn, 2010; Schwandt and von Wachter, 2019; Rothstein, 2023)
- Mechanisms – skill mismatch, foregone occupation- and industry-specific human capital (Liu et al., 2016; Brunner and Kuhn, 2014) – apply here too
- Doubly so if GenAI complements experience (Autor and Thompson, 2025)

GenAI and Educational Decisions

AI Changes Both the Benefits and Costs of Education

Automation penalty

Tasks become cheaper to automate, lowering the earnings premium in exposed fields.

Expertise complementarity

Advanced skills may raise the value of working with AI.

Effort costs

AI may also make coursework in exposed fields easier to complete.

A field loses appeal when the lasting earnings loss students expect from AI outweighs the effort AI saves them.

How Can Students Adjust to Automation?

We consider two strategies:

Pivot

Choose a less-exposed major, course bundle, or graduate field.

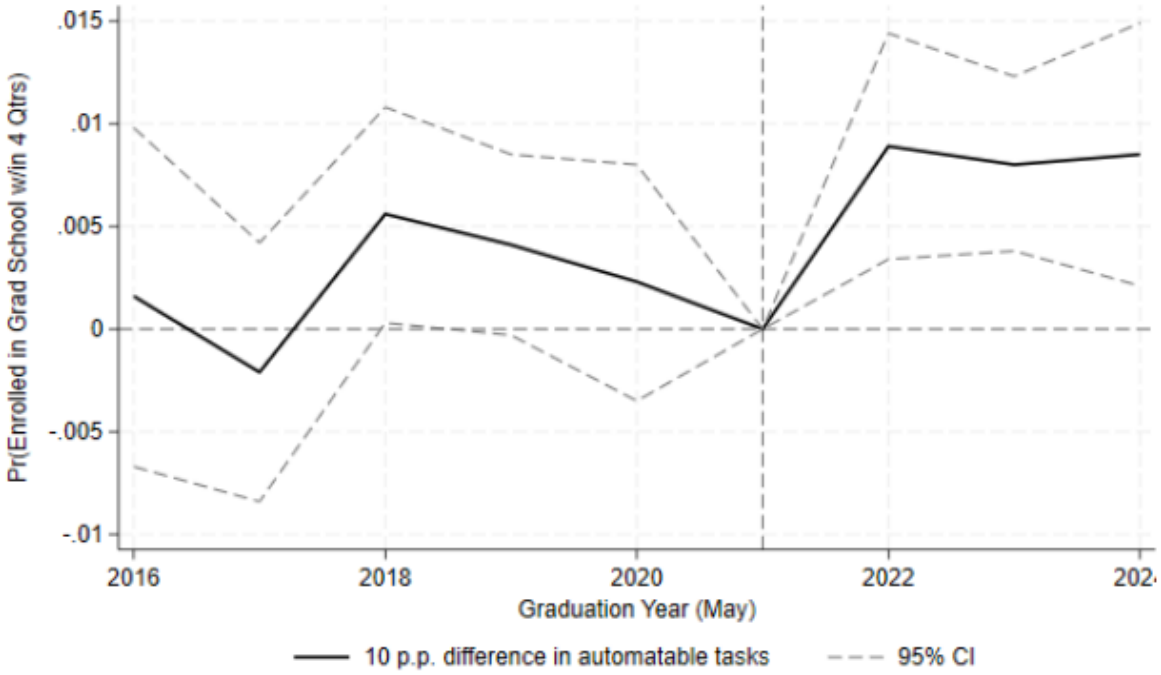
Upskill

Deepen expertise through advanced coursework or graduate study in an exposed field.

The dominant strategy depends on substitution, complementarity, the persistence students expect in the technology shock, and how AI changes the effort costs of coursework.

Switching costs: Costs of switching fields increase in seniority $\Rightarrow$ adjustment cannot happen instantaneously

Graduates from Exposed Majors Returned to School



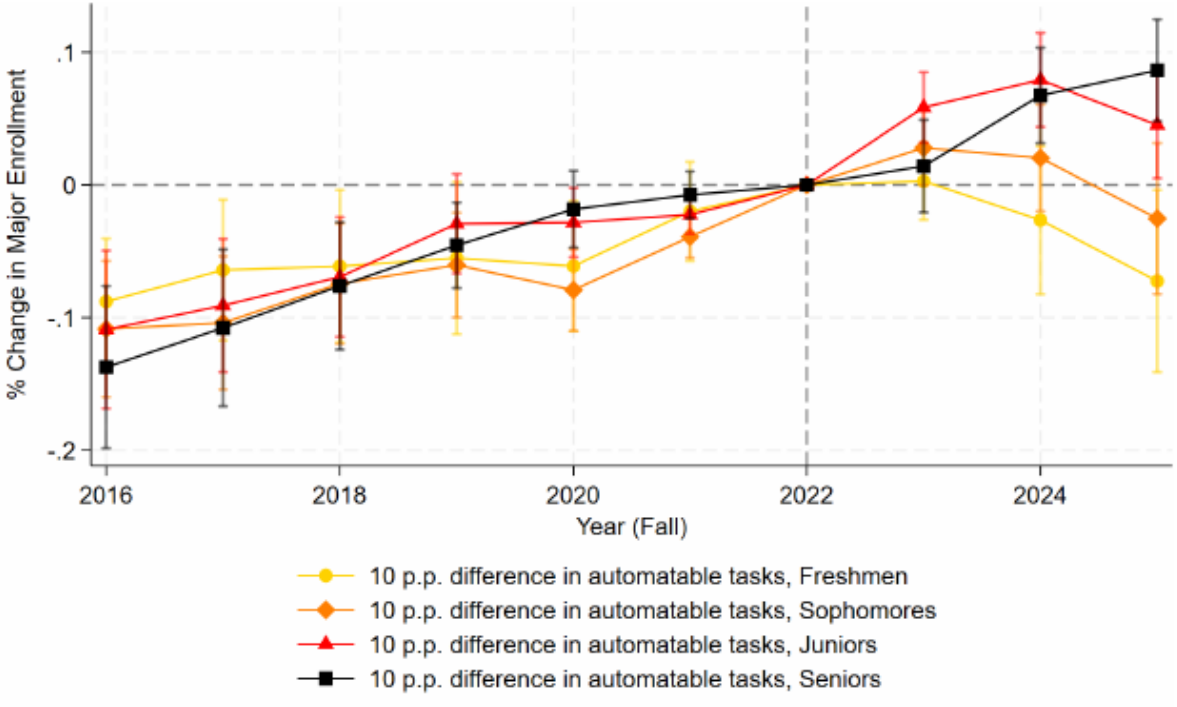
Pr(Enrolled in a graduate program within a year of graduation)

2024: +0.9 p.p. ↑ 6%

. . . but Kept Studying the Same Fields

- No change in *MajExp* of the *graduate* program in which they enrolled
- 66% of 2024 CS graduates chose a CS program (68% pre-ChatGPT)
- Consistent with an **upskilling** response

Post-GPT Uni Entrants Pivoted from More-Exposed Fields



Fall enrollment counts by classification, Poisson

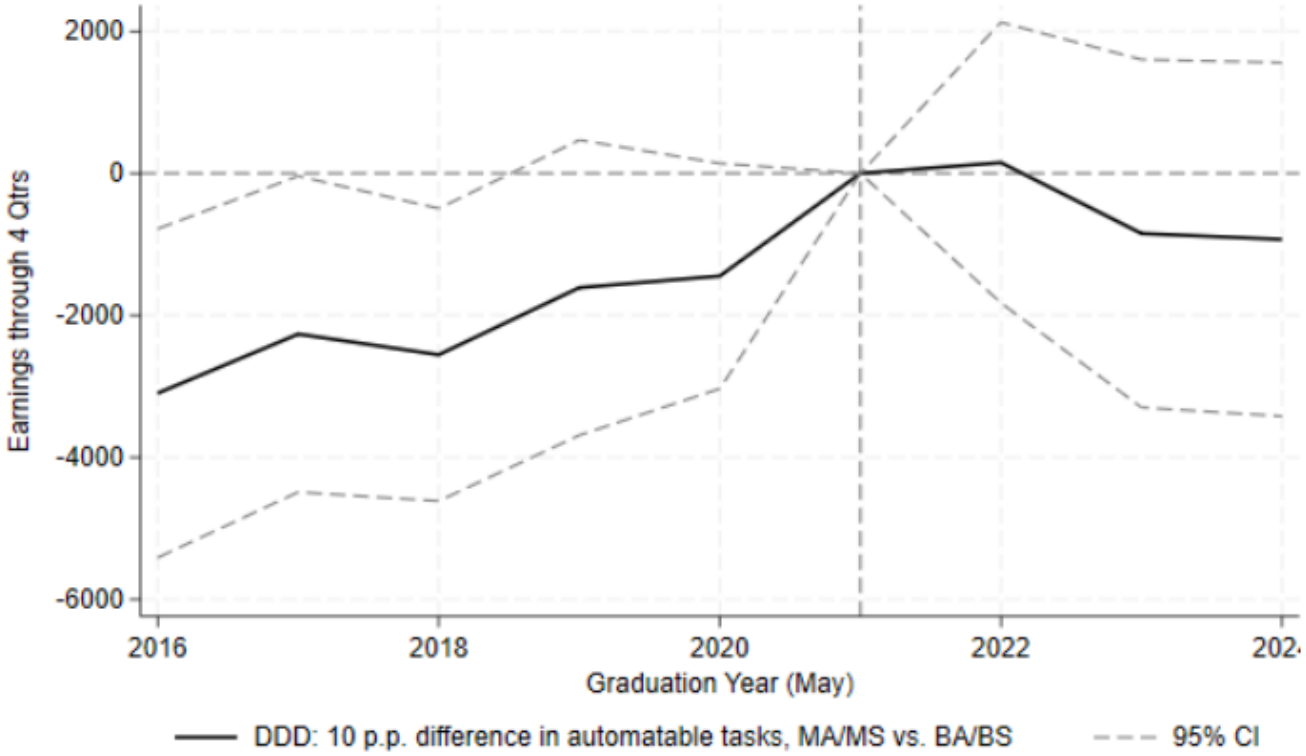
Freshmen: $\downarrow$ 6%, Fall 2022 to Fall 2025

Mimics delayed enrollment response to prior field-specific demand shocks (Weinstein, 2022; Conzelmann et al., 2023)

Do Adjustments Pay Off?

*indirect suggestive evidence

Master's Recipients from More-Exposed Fields Experienced Similar Earnings Declines



Earnings | employed all four quarters, new MA/MS. new BA/BS (DDD)

Suggests master's degrees did not yield additional complementarity

Course-Level Upskilling vs Pivoting

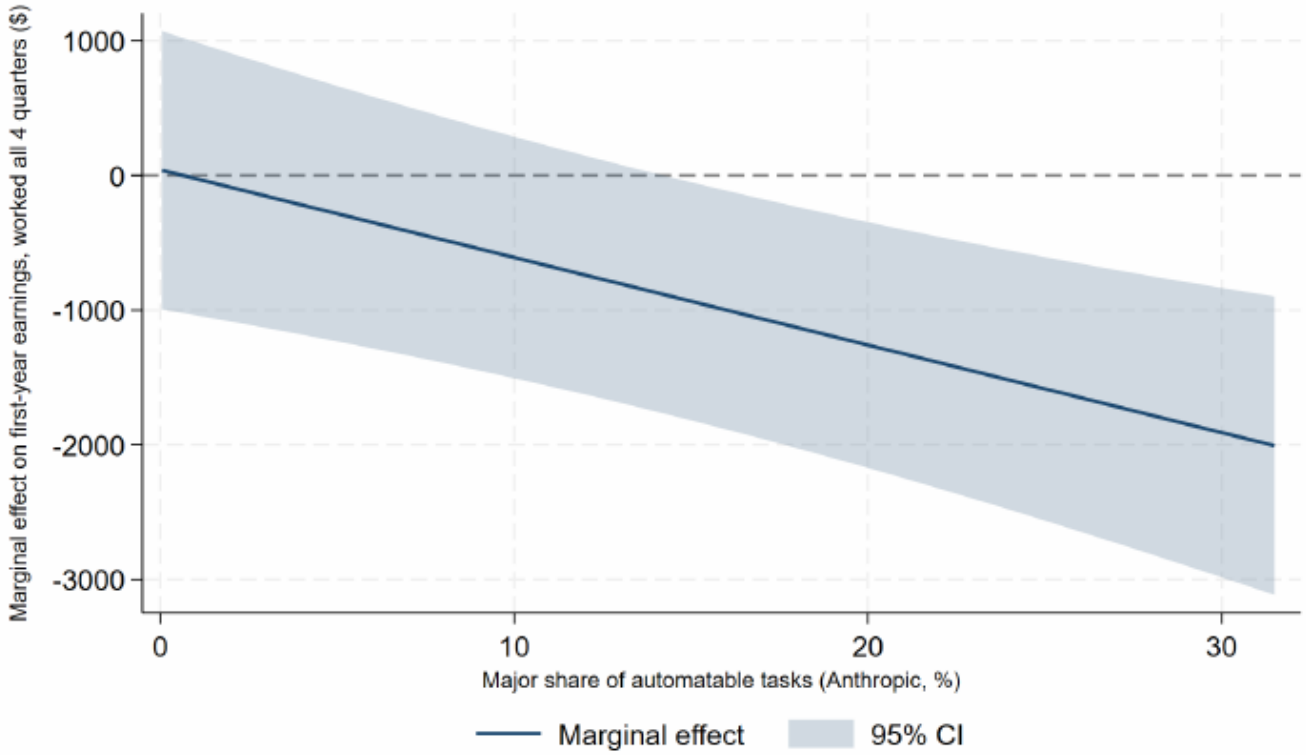
Student A: CS major	Student B: CS major
Intro to programming	Intro to programming
Data structures	Data structures
Machine learning	Intermediate microeconomics
Database systems	Social psychology

More exposed than a typical CS major — ■ Course in a highly exposed field

Less exposed than a typical CS major — □ Course in a less exposed field

Did students whose courses were less exposed to AI fare better?

More-Exposed Course Mixes Associated With Larger Earnings Losses



In a highly exposed major, a less-exposed course mix is associated with about $1,900 more in first-year earnings, roughly a quarter of the AI earnings penalty.
$\Rightarrow$ suggests returns to pivoting rather than upskilling

Conclusion

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Widespread labor market disruption has not arrived – but the GenAI transition is causing varying degrees of harm across three groups

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Widespread labor market disruption has not arrived – but the GenAI transition is causing varying degrees of harm across three groups

1. **Recent graduates from exposed majors:** Deteriorating earnings and employment, persisting into year two; graduate school in the same field has not paid off
2. **Students in college at the time of the shock:** Made little or no adjustment to majors or coursework $\Rightarrow$ similar harm may reach the 2025 and 2026 cohorts
3. **Students entering after the shock:** Appear to be internalizing the decline in demand; their shift away from exposed fields may buffer them

Open Questions

Our results are consistent with GenAI operating as a *normal* technological demand shock – but the technology plausibly carries broader implications

- **Learning.** GenAI can automate out-of-classroom assignments; what happens to human capital actually acquired? (Light, 2026)
- **Substitution for schooling.** Does democratized access to expertise substitute for formal education?
- **Institutions.** Do colleges reinstate human expertise through curriculum? (Lipowski et al., 2024)
- **Persistence.** Whatever the path, the literature on initial labor market conditions (e.g., Arellano-Bover, 2024) says the cohorts caught in the transition matter

Thank you!

tucker.smith@dal.frb.org
www.tuckerwsmith.com

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The Skill Premium in Times of Rapid Technological Change

Tarek Hassan[1] Aakash Kalyani[2]
Pascual Restrepo[3]

[1]Boston University

[2]Federal Reserve Bank of St Louis

[3]Yale University

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Labor Markets & Structural Transformation in Times of Change | Washington, DC, November 2026

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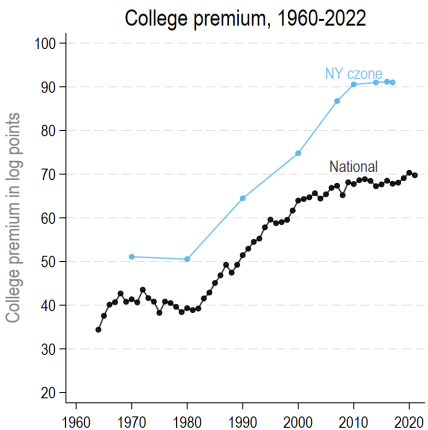
Motivation



- Major driver of wage inequality: College premium increased dramatically since 1980.
  - 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

Model on One Slide

- $m(b)$: mass of technologies introduced at birth date (cohort) b.

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$$m_t(u)$$

where $u = t - b$.

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

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- Exponential growth in cohort-specific productivity

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

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

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

Solving the Model

(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

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

Solving the Model

(1) Income Clearance

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

(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

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

Measure m (technology arrival), $\alpha(u)$ (college share by age), and $z(u)$ (life cycle) **from the full text of patents and job postings**

In the Long Run, . . .

Proposition 1/2: balanced growth path (BGP)

Consider a BGP in which 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:

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

- **The skill premium is independent of m**
- **Depends only on $\alpha(u)$ and $z(u)$**: pace of standardization vs. gaining or losing market share

– (and, as usual, the supply of skills $\frac{h}{\ell}$)

An Increase in Technology Arrival, m, ...

Proposition 2/2: 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:

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

- **Increases the skill premium — temporarily**, and more persistently 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)

Key idea:

- When inventors create a new technology, they also **create the language** used to refer to it.
- Identify this new language in USPTO patents; use Wikipedia to map each set of newly created phrases to a specific "technology."
- Label using the title of the Wikipedia page.

$\Rightarrow$ List of 6,259 technologies that emerged between 1941 and 2006.

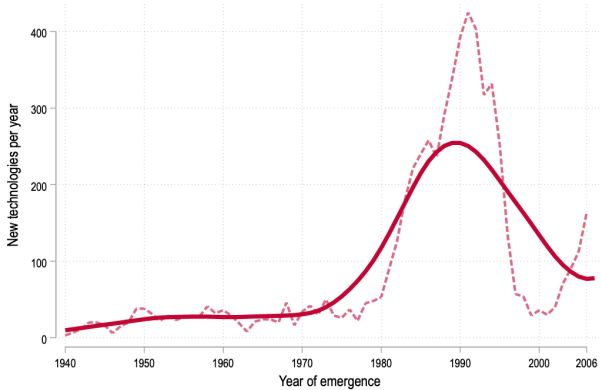
- With the new language in hand, **create data on each technology**:
  - Assign emergence years based on accelerated incidence in patenting $\rightarrow m$
  - Track in Lightcast job postings (2010–2023) $\rightarrow \alpha(u)$, $z(u)$

Wikipedia | Patent examples | Job postings

Examples

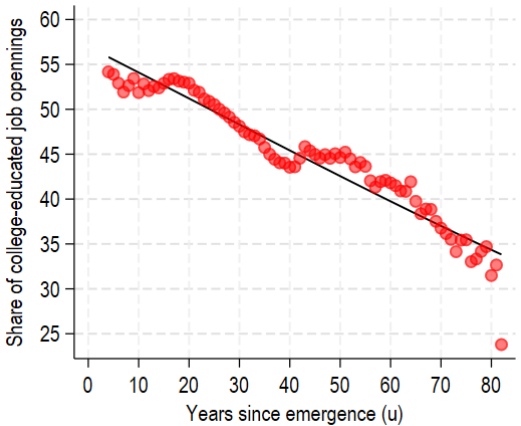
Emergence Year	Technology	Phrases
1941	Audio amplifier	...
1946	Lateral flow test	...
1951	Pulse generator	...
1955	Injection moulding	...
1960	MOSFET	...
1962	Printed circuit board	...
1967	Optical fiber	...
1974	Analog-to-digital converter	...
1979	Digital image processing	...
1982	Barcode	...
1984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

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



- **Extraordinary surge in number of newly emerging technologies 1980–1995.**
- Highly robust to alternative measurement strategies.

Fact 2: New Technologies Are Skill-Intensive, Then Broaden

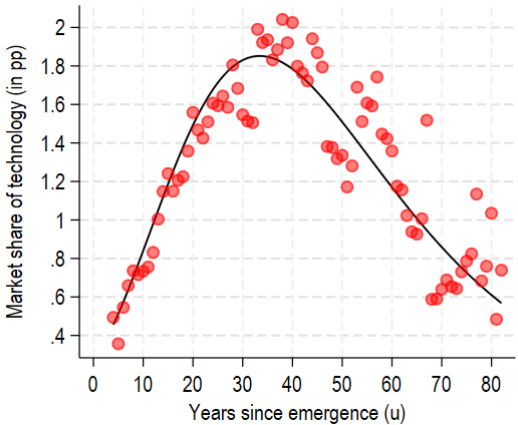


- Robust to cohort effects and excluding ICT.

- **57% of jobs working with newly created technologies require a college degree** — vs. 34% for 80-year-old technologies.
- **"Skill broadening" over time**: as technologies age and standardize, they open up to non-college workers.
- New technologies **disproportionately create opportunities for high-skill workers for decades**.
- **Use this slope to estimate** $\alpha(u)$, the skill intensity of a technology of age u, given $\gamma = 1.4$ (Katz and Murphy, 1992):

$$\frac{h(u)}{\ell(u)} = \frac{\alpha(u)}{1-\alpha(u)} \left(\frac{W_h}{W_\ell}\right)^{-\gamma}$$

Fact 3: Technologies Take Decades to Diffuse in Labor Market



- **New technologies start small**: 0.4% of job postings when young.
- **Employment peaks 35 years after emergence**, at 2% of job postings: full deployment takes decades.
- **Then a gradual decline**: old technologies lose market share to new ones.
- **Use this life cycle to estimate** $z(u)$, the productivity of a technology of age u, given $\sigma = 3.5$ and $g = 2\%$:

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

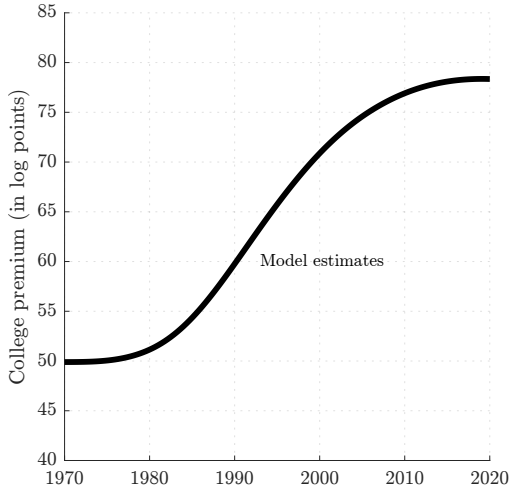
Dimension 1: The Skill Premium over Time

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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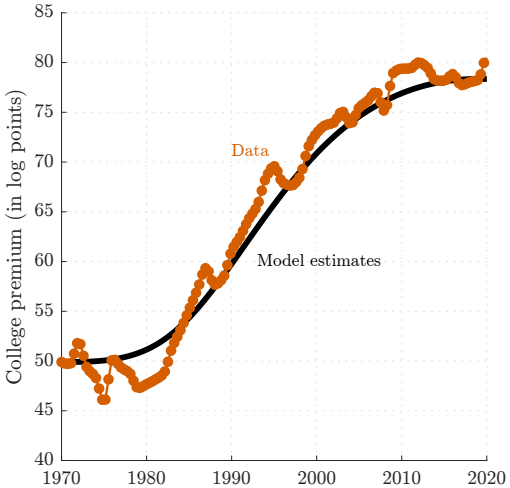

Results: Skill Premium over Time

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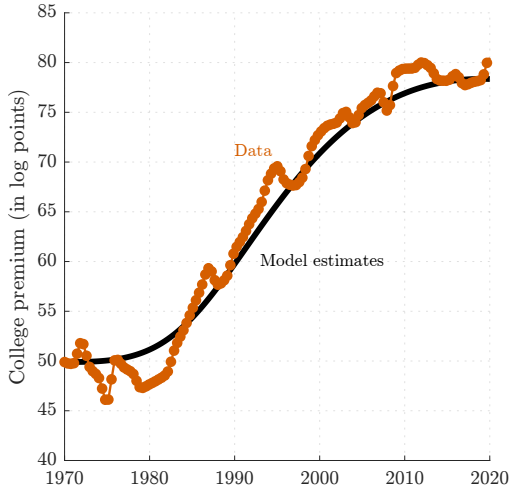
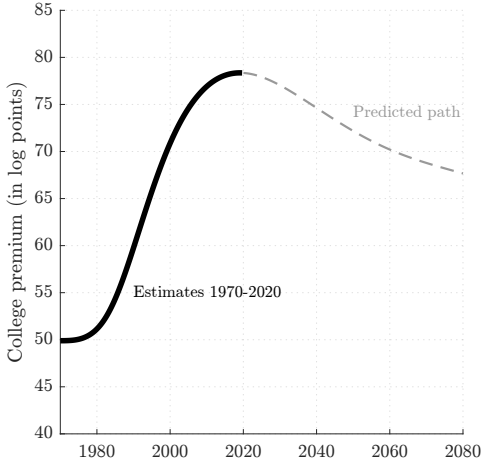
- Results:
  - 28 log-point (32%) increase in the college premium
  - The mechanism explains one-third of the rise in relative demand for college workers.

Wages, output & TFP | College supply



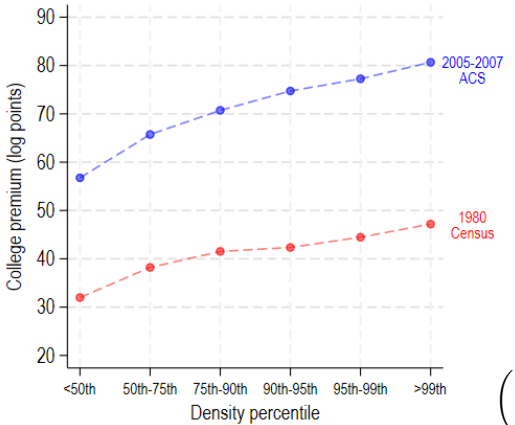
The Future of the Skill Premium



- **Absent further changes, the college premium reverts halfway to its pre-1980 level by 2080.**

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 the 2000s.

Model extension:

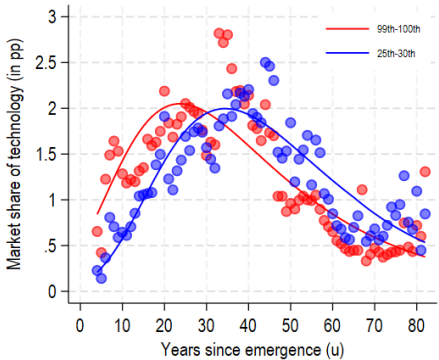
- Cities differ by density $d \in [0, 1]$
- **Key addition:** technology of age u diffused to city d with probability $p(d, u)$
- Skill premium under $\gamma = \sigma$:

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

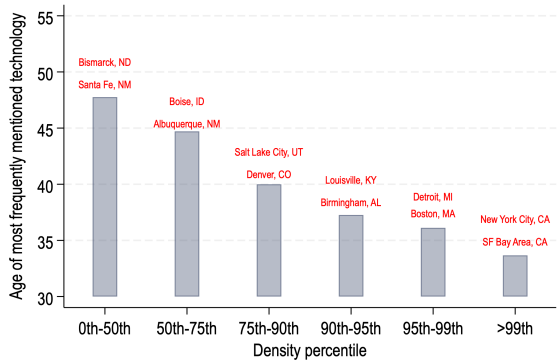
Dense Places Use Younger Technologies

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

Market shares by density



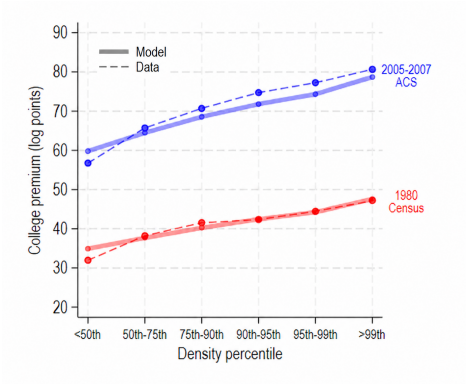
Age of most frequently mentioned technology



Regional technology life cycle

Results - College premium by density

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

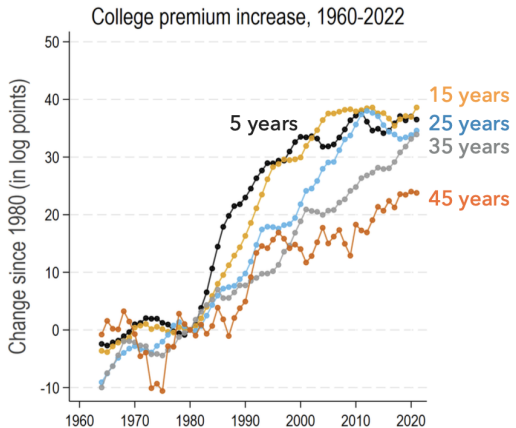


Skill premium (model vs data)

- **The same model matches the urban college premium, in levels and in changes, without targeting either.**

Dimension 3: The Skill Premium across Cohorts

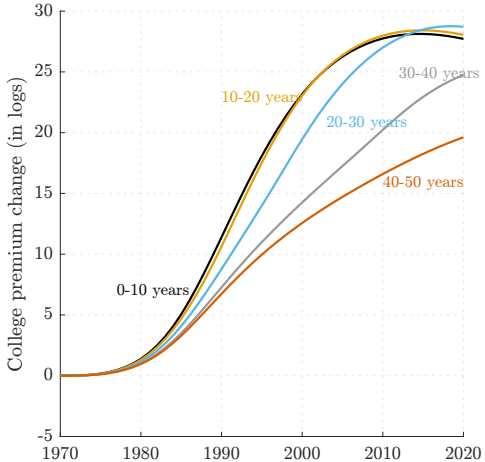
Cohort Effects in College Premium



- **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 the college premium

Changes in Skill Premia since 1970 in the model



Conclusion

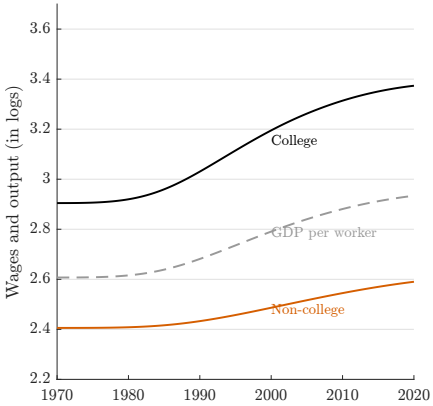
- The invention of new technologies and their diffusion in the labor market offer a compelling explanation for the dynamics of wage inequality.
- **Novel, text-based data on technology arrival and diffusion** show:

1. An extraordinary surge of new technologies between 1980 and 1995.
2. A technology's share of jobs peaks 35 years after it emerges.
3. Dense cities use newer technologies: 14 years younger in the top 1% densest locations than in the bottom 50%.

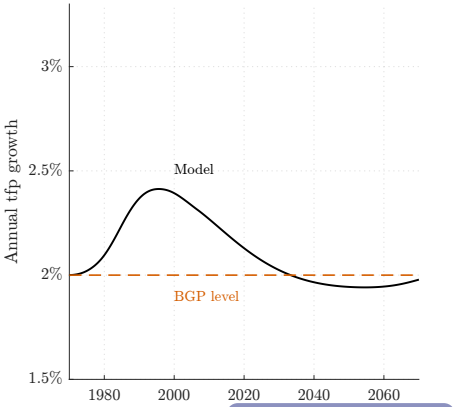
- **A simple model in which young, educated workers have a comparative advantage in using newer technologies** explains variation in the skill premium over time, across space, and across age groups.

Additional result: Wages, output, and TFP

Wages and output levels



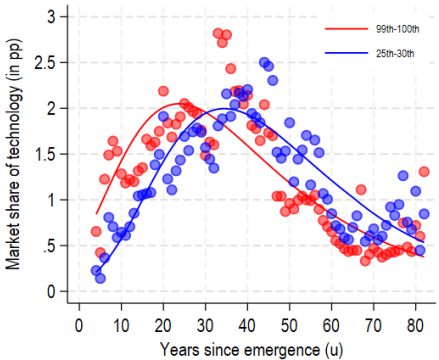
TFP growth



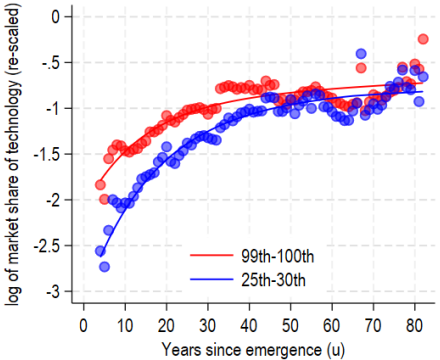
Back to skill-premium results

Regional technology life cycle

Employment share per technology

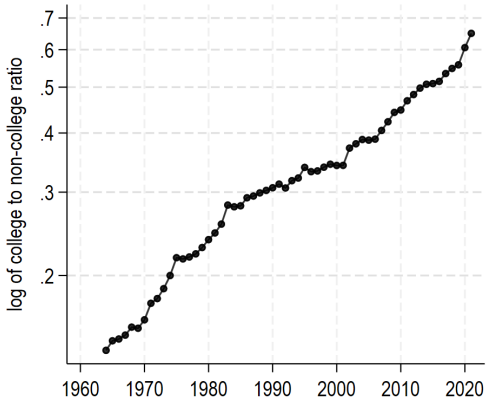


Re-scaled employment share



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, -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

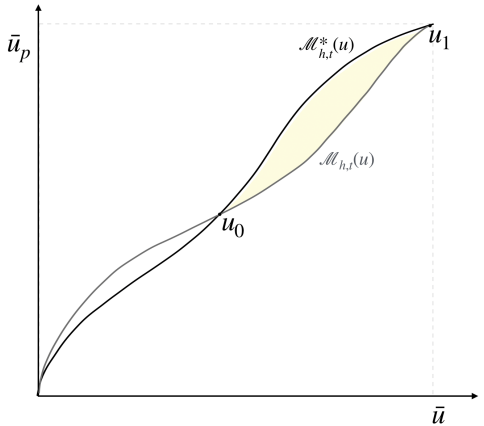
Decomposition robustness across values of γ

	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

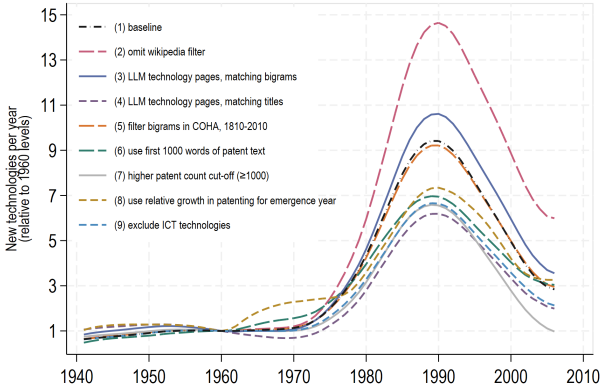
Skill broadening - variation in specifications

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

Back

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



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

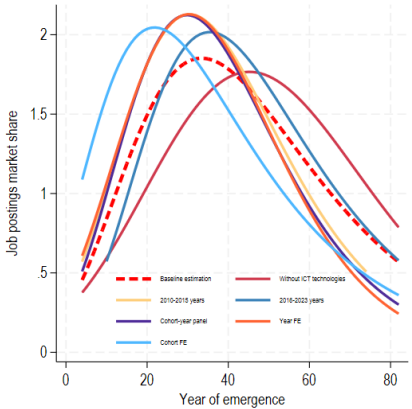
$z(u)$ estimates - variation in specifications

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)
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

Back

Robustness: implied employment shares by technology age



Back

Robustness of regional estimates

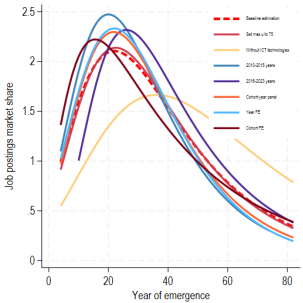
Table: **Joint estimates of $z(u)$ and $p(u,d)$ plus robustness checks.**

						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

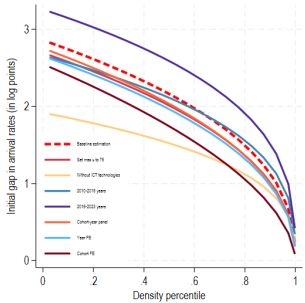
Back to spatial measurement

Robustness: diffusion across space

Panel A: Employment shares in highest-density locations

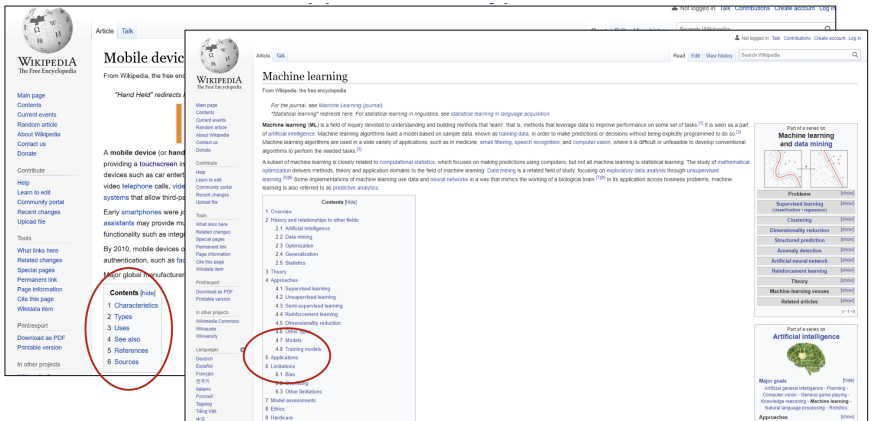


Panel B: Arrival gap across locations (log points)



Back to spatial measurement

Wikipedia technology page



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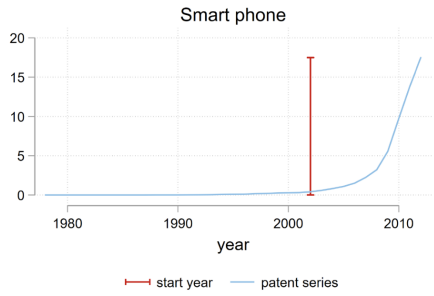
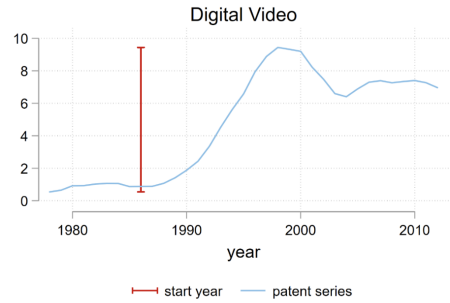
Emergence year example





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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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Can we sign "Exposure"?

Discussion of:

Hassan, Kalyani & Restrepo · Dodini, Smith & Xu · Jacobs & Canedy

Tito Boeri

Bocconi University

IMF-OECD-PIIE-World Bank Conference
Washington, November 17-18, 2026

Three papers at different stages of the adjustment chain

STAGE 1 - New technologies arrive: pace of creation, speed of standardization
STAGE 2 - Skill demand shifts: who gains, where, and for how long
STAGE 3 - Students re-optimize: majors, courses, graduate school
STAGE 4 - Displaced workers adjust: retraining, occupational reallocation

- Hassan, Kalyani & Restrepo - stages 1-2, 1970-2080 Summary HKR
- Dodini, Smith & Xu - stages 2-3, 2016-2025 Summary DSX
- Jacobs & Canedy - stage 4, 2013-2023 Summary JC

3 key issues for policy

1. Who is exposed? Measurement
2. Who benefits and who loses (the sign)? Causality
3. Are potential losers adjusting? Policy is helpful?

1. Who is Exposed?

- **HKR:** Wikipedia to separate technological vintages; Bigrams to measure the intensity of different technologies across patents and job postings
- **DSX:** Application to job postings (occupations) and major choices (bundles of occupations) of existing exposure to AI metrics
- **JC:** Routine Task Intensity as metric for computerization-driven automation (more than AI)

Measurement problems:

- **HKR**: This time is different.
- **DSX**: Problematic aggregation from tasks to occupations to bundles of occupations, to course-level...
- **JC**: Computerization is not AI

Other measurement problems (and some suggestions)

- Retraining index (**JC**) is a performance metric, closer to a scorecard of how participants fared, not informative about which displaced workers to steer toward AI-intensive training.

⇒ *Find a control group (see also causality)*

- Too short history of the shock. (**DSX, JC**)

⇒ *In some occupations (e.g., software development) AI tools were already in use before ChatGPT.* ***Find canary in the coal mine groups*** e.g., GitHub Copilot available in June 2022 when DSX find decline coming "too early".

- Postings are not hires (**HKR, DSX**). Lightcast records what is asked for, not what is done.

⇒ *Record linkage with administrative data (social security archives) to measure filled vacancies*

2. Who benefits and who loses?

- Past waves · **HKR**: Young, educated workers were the early adopters The premium rose first for the young and in dense cities; older workers caught up as technologies aged.
- Generative AI · **DSX**: Young, educated entrants are the first to lose -4% first-year earnings per 10 pp of exposure, consistent with evidence that adopting firms cut junior hiring while senior jobs hold.
- Not necessarily a contradiction: AI substitutes for *codified* knowledge, which is what entrants bring, and complements *tacit* experience. HKR's age gradient could invert (Brynjolfsson et al ,2026)

$\Rightarrow$ *Possible test: Do AI-linked job postings and new occupation titles (prompt engineers, AI specialists, etc) skew young and college-educated? Do they carry a wage premium decaying with vintage (as it gets standardized)? Is the decline in entry level hiring for tasks that are being automated by AI? Is there a young-worker advantage in using AI on the job? Is it outweighed by the hiring decline in exposed entry-level roles?*

Causality and Impact

HKR:

- Calibration from aggregate time-series: matching the timing is not a test
- 2/3 of demand shift is still a residual

⇒ *Which parameter(s) of the model would change with AI? What would happen to the wage premium?*

DSX:

- Shift-share instruments: use of Claude (measured in Fall 2024) is endogenous. Results hold with the human-rated (potential) exposure measure but not the GPT-4-rated one.
- Many confounders (remote work, federal layoffs, Trump uncertainty....)

⇒ *Check parallel trend assumption with earning (before Covid) series? Also for remotability LightCast measures available since 2010*

Further identification problems

DSX:

- Not only interest rate hike but also tech-hiring bust; computer science drives the exposed tail?

JC:

- No counterfactual; the sample keeps only those with an exit and post-program wages.

$\Rightarrow$ *Matching to nearest neighbor similarly exposed to AI but not receiving retraining?*

- Occupation-level index covers 0.7% of non-trainees, 7.6% of trainees
- Ashenfelter dip $\rightarrow$ mean reversion: (acknowledged) a 4-quarter window misses where training pays off. Again matching control could help out

3. Adjustment of People

Why don't students leave exposed fields?

- **Lower effort cost:** AI makes exposed coursework easier. This is the authors' mechanism, but it is not yet tested: grades, time to degree and course failure rates would show it.
- **Weak signals:** The demand shock is 1-2 years old; exposure measures disagree; AI compresses grades, so the signal to employers is noisier too.
- **Rational waiting:** If, as in HKR, demand shifts are long-lived but temporary, grad school is a shelter from scarring rather than a mistake.

> Bad investment or option value? It depends on whether the shift is *persistent*, and no paper can tell us that yet.

Adjustment of Policies: WIOA was built for another shock

	WIOA today (JC)	**Likely AI-displaced**
Who	Low earners; trainees earn ∼half of non-trainees before entry	Graduates, mid-career, mid-high wages
Weakest results	Bachelor's 0.45, dislocated workers 0.49, high-wage states	Exactly this group
Target	Less routine work	Non-routine cognitive work is now exposed
Scale	∼500k a year; ∼200k vouchers; ∼$500m	Potentially far larger, and faster

> A floor, not a ladder, and aimed at a target that is moving.

Five possible implications for policy

1. **Measure before targeting**
   Link education, earnings and benefit records in near real time, as the Texas data do; do not write exposure lists into policy. **Use AI to monitor and predict AI**

2. **Protect the entry ladder**
   Graduate traineeships and apprenticeships where AI cuts junior hiring; **early scarring is long-lasting**.

3. **Training to AI-complementary skills**
   Hyman-Lahey-Ni-Pilossoph (2026) rise of wages in exposed occupations if training to AI-complementary skills. Possible with apprenticeships and customized training (tied to employers).

4. **Pair training with insurance**
   For educated, mid-career losers, wage insurance and income support, not vouchers alone. Prepare social security (with AI) to react quickly

5. **Inform, don't steer, students**
   Publish outcomes by field; redesign grading so degrees keep their signal value.

Takeaway

Past technologies took decades to absorb. AI's distinctive challenge may be speed, and our adjustment institutions are slow.

Decades to standardize a technology (HKR)

Sticky education choices (DSX)

Little reallocation through retraining (JC)

Suggestions to the authors

Hassan, Kalyani & Restrepo

- Use education required in each posting, not occupation averages
- Out-of-sample test: fit to 1995, forecast 2000-20; other OECD countries
- AI scenarios: a burst in creation with faster standardization and a smaller college edge

Dodini, Smith & Xu

- Separate out-of-state moves from non-employment
- Results without computer science; placebo on the 2019-20 tech cycle
- Test the effort-cost channel: grades, completion, time to degree
- Heterogeneity by GPA and ability

Jacobs & Canedy

- A comparison group: UI claimants outside WIOA, matched on pre-entry earnings
- Report wage and task components separately; the weights drive the index
- Add AI exposure as an outcome: did "successes" move into AI-exposed jobs? See Hyman et al (2026) and AI-retrainability index.

What each paper does and finds

Hassan, Kalyani & Restrepo (HKR)

Design. Vintage model: the educated learn new technologies faster (Goldin and Katz); the edge fades as technologies standardize. Calibrated on 6,259 technologies (patent text) and 300m job postings.

- Technology creation rose 7-10$\times$ in the 1980s, then slowed
- College share of jobs: 57% for new technologies, 34% at age 80
- Explains $+28$ lp in the premium (1/3 of the demand shift), $\sim$70% of the urban gap

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What each paper does and finds

Dodini, Smith & Xu (DSX)

Design. Texas public-university graduates 2016-23 linked to UI earnings, plus Lightcast. Event study with continuous "dose": AI exposure of the major.

- $+10$ pp exposure $\rightarrow -4\%$ first-year earnings (half jobs, half wages)
- Postings for exposed occupations -5% in a year, $\sim -10\%$ by 2025
- No flight from exposed fields: more grad school in the same field

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What each paper does and finds

Jacobs & Canedy (JC)

Design. 23m WIOA (Workforce Innovation and Opportunity Act) participation records, 2017-23. "Retrainability Index": wage change (50%) plus fall in routine task intensity (50%). Descriptive, plus XGBoost.

- $\sim$5% get formal training; 45% return to their prior industry
- Gains are wage catch-up, rarely a move away from routine work
- Apprenticeships do best (0.71); age penalty 0.57 $\rightarrow$ 0.41

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