

Beyond the Race between Education and Technology (RBET)

- 1. RBET and U.S. Wage Structure Changes, 1825 to 2025
 - (a) Goldin-Katz (2008 *RBET*) and Autor, Goldin, and Katz (2020 *AEA P&P*) show RBET works well for 19th and 20th century; secular rising demand for more educated workers from SBTC combined with increased access to education; institutions (unions, minimum wage) also key roles
 - (b) Rising education returns drive post-1980 inequality increase and decreasing education returns drive 1910 to 1950 narrowing
 - (c) RBET still relevant but education returns less of story for 2000 to 2023 (33%) than 1980 to 2000 (75%) RBET needs tweaks for 21st century
 - (d) Task-Based Framework, Augmentation vs. Automation Innovations, Bundling Tasks into Jobs/Occupations and Impact on Expertise
- 2. Artificial Intelligence, Remote Work, and the 21st Century Labor Market



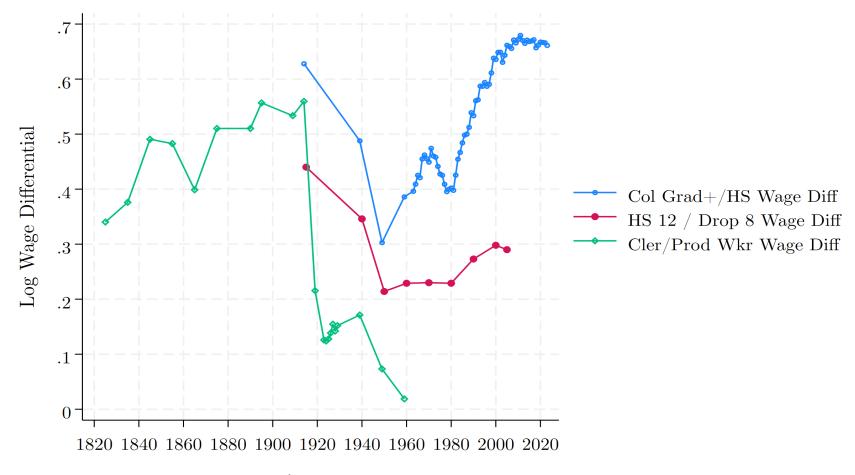


Figure 1: Education/Skill Log Wage Premia, 1825-2023

Notes: Updates Figure 1 in Autor, Goldin, and Katz (2020 AEA P&P) to include data through 2023.

Importance of Rising Returns to Education

Table A3: Contribution of Changes in Returns to Schooling to Increased Hourly Wage Inequality, 1980 to 2023

| Panel A: | Var ln(w) | 90-10 | K to 12 | College | Post- |
|--------------|-----------|-----------|-------------------------------------|---------|---------|
| | | | | | College |
| 1980 | 0.250 | 1.247 | 0.063 | 0.077 | 0.067 |
| 2000 | 0.315 | 1.436 | 0.075 | 0.126 | 0.131 |
| 2023 | 0.349 | 1.496 | 0.051 | 0.134 | 0.167 |
| | | | | | |
| Panel B: | Change in | Change in | Education Return Contribution Share | | |
| | Var ln(w) | 90-10 | Var ln(w) | , | 90-10 |
| 1980 to 2000 | 0.065 | 0.189 | 0.746 | | 0.649 |
| 2000 to 2023 | 0.033 | 0.059 | 0.334 | | 0.514 |
| 1980 to 2023 | 0.098 | 0.248 | 0.541 | | 0.617 |

Notes: Updates Table A.3 of Autor, Goldin, and Katz (2020) to 2023

Two Major Components of Increase in U.S. Wage Inequality since 1980:

- (1) Increased returns to post-secondary schooling (54 percent)
- (2) Rising Wage Inequality Among the College Educated (rise of Top 1%)

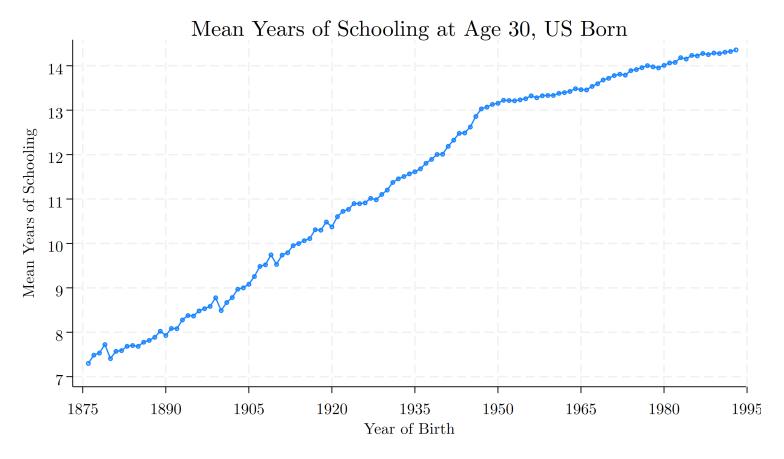


Figure 2: Mean Years of Schooling at Age 30 for the US Born, 1876 to 1993 Birth Cohorts

Notes: Extends Figure 2 in Autor, Goldin, and Katz. (2020 AEA P&P) to include data for cohorts 1988–1993 using 2019–2024 MORG CPS files.

Race Between Education and Technology in the Long Run I

- Rapid long-run secular growth in relative demand for more educated workers from SBTC since 1820
 - Industrial era: Shift Artisanal Shop to Factory erodes artisanal skills but increases demand for mass expertise (high school graduates in production/clerical jobs)
 - Information era: Computerization erodes routine clerical and production skills & shifts demand to elite expertise (college plus) of expert knowledge and high stakes decision making (rise of decision jobs) leading to labor demand polarization; classical computing needs instructions – value of tacit knowledge
 - Artificial Intellgence Era: Machine learning permits automation of non-routine tasks What expertise get eroded, what expertise augmented and what new expertise gets demanded?
- Post-WWII acceleration in relative demand for college workers; but similarly rapid demand pre-WWII for high school graduates
- Variation in rate of growth of supply of skills is key: with an acceleration around 1910 with the high school movement, further acceleration in 1970s with baby boom, and sharp deceleration post-1980
- College/non-college demand shift shows acceleration in 1980s and then slowdown 1990s-2000s

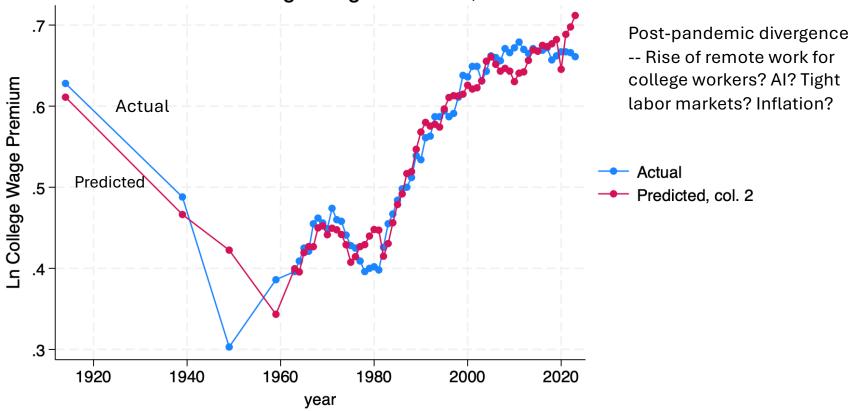


Race Between Education and Technology in the Long Run II

- Impact of computers is more subtle than standard monotonic SBTC view – manual vs. routine vs. abstract tasks -- shift to polarization of labor demand (Autor, Levy and Murnane 2003 QJE)
- 2000s a puzzle slowdown in demand for cognitive/abstract skills) but rise in demand/returns to social*abstract skills (Deming 2017 *QJE*). Rise of remote work for college workers post-pandemic.
- Supply-Demand-Institutions add role of minimum wage and reduces demand slowdown since 1990s in Vogel (2024 QJE)
- Emerging research on automation, robots, new work, expertise, and AI – Acemoglu-Restrepo; Autor et al. (2024), Autor-Thompson (2025), Hampole et al. (2025), ...

LABOR MARKETS IN TRANSITION: DEMOGRAPHICS, PRODUCTIVITY AND MACROECONOMIC POLICY

Actual vs. Predicted College Wage Premium, 1914 to 2023



Source: Goldin and Katz (RBET 2008; updated to 2023)

Table 2: Changes in the College Wage Premium and the Supply and Demand for College Educated Workers: 1914 to 2023 (100 × Annual Log Changes)

Post-1980 vs. 1939-79: 3/4 supply deceleration vs. 1/4 demand acceleration

| | Changes in the Relative Wage | Changes in Relative Supply | Changes in Relative Demand |
|-----------|---------------------------------|-------------------------------|-------------------------------|
| | | | $(\sigma sv = 1.59)$ |
| | (1) | (2) | (3) |
| 1914-1939 | -0.56 | 2.57 | 1.68 |
| 1939-1959 | -0.51 | 2.63 | 1.82 |
| 1959-1979 | 0.07 | 3.51 | 3.63 |
| 1979-1999 | 1.19 | 2.28 | 4.18 |
| 1999-2023 | 0.10 | 1.91 | 2.06 |
| | | | |
| 1939-1979 | -0.22 | 3.07 | 2.72 |
| 1979-2023 | 0.59 | 2.08 | 3.02 |
| 1914-2023 | 0.03 | 2.56 | 2.61 |

Notes: Updates Table A2 of Autor, Goldin, and Katz (2020) to 2023. The underlying data are from the 1915 Iowa State Census, 1940 to 1970 Census IPUMS, and 1964 to 2024 March CPS.

Why Interpret Trends as SBTC?

- Rapid Within-sector (and within-plant) skill upgrading despite rising relative skill prices
- Technology-Skill & Capital-Skill Complementarity: Positive Effects of Technology Indicators (Computers, R&D, New Equipment) on Skill (Education, Occupations, Tasks) of Work Force in Levels, Changes, and Acceleration (by Industries and Establishments)
- Case Studies of Technology (IT) Investments for financial services, auto repair, valve manufacturing, steel, (Autor-Murnane-Levy 2002 *ILRR*; Bartel-Ichniowski-Shaw 2007 *AER*)
- New Work: New job titles positively related to occupational exposure to labor augmenting innovations and negatively related to labor automating innovations (Autor et al. 2024 *QJE*). Majority of current work is in new job specialties introduced after 1940
- Direct Evidence and Natural Experiments
 - Broadband introduction in Norway (Aaker, Gaarder & Mogstad 2015 QJE)
 - Geographic variation in industrial robot exposure (Acemoglu-Restrepo 2109 JPE)
 - Differential exposure to automation-based task displacement by education-demographic groups explains wage structure changes for 1980 to 2016 with "so so" automation →small productivity gains but large labor demand and wage impacts (Acemoglu-Restrepo 2022 *EMA*)
 - Task automation impacts on occupational wages and employment depend on whether increase or decrease occupational expertise (Autor-Thompson 2025) and on share of tasks ("concentration") in occupation directly affected (Hampole et al. 2025)



Al, Remote Work, and the 21st Century Labor Market

- Classical computing required explicit and detailed instructions for how to transform inputs into outputs: when engineers write code to perform a task, they are codifying that task. Routine clerical and production tasks more susceptible to computerization with classical computing.
- ML & AI infer instructions from examples (big data) & can learn to do tasks even where no instructions exist (writing emails, analyzing data, or creating presentations) so can automate non-routine tasks
- Early Evidence of Al Impact on the Labor Market
 - Generative AI increases productivity in professional writing tasks (Noy-Zhang 2023 Science), customer support (Brynjolfsson-Li-Raymond (2025 QJE), software developers (Cui et al. 2025), & Uber/taxi drivers (Kanazawa et al. 2022) with larger gains for novice and less skilled workers
 - Humlum-Vestergaard (2025) little impact yet of LLMs on wages & hours workers in Denmark
 - Johnston-Makridis (2025) find ChatGPT release modestly improves wages & employment for in sectors
 with greater LLM augmentation exposure and negative effects with more substitution exposure;
 Eckhardt and Goldschlag (2025) no evidence of impacts so far on employment or unemployment
 multiple measures of AI occupational exposure
- Al & Education: Personalization, Teaching at the Right Level vs. "Cheating" & Screen Time Concerns
- Remote Work sharply increased with pandemic & persisted for college workers (40%) vs. HS workers (<10%) with issues in mentoring of younger workers & parental resources for children

