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Beyond the Race between Education and Technology

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U.S. wage inequality increased substantially from 1980 to around 2015 and, even with some modest narrowing over the last decade, remains at a historically high level. Rising educational wage differentials and a growing divide between college and non-college workers have been key drivers of greater wage disparities in the United States and other OECD countries. Technological advance from the information revolution, computerization, and the emerging rise of artificial intelligence (AI) has been viewed by many as a culprit behind rising inequality. Technological change clearly impacts the demand for different types of workers, skills, and tasks. And there is much evidence that the adoption and diffusion of major general-purpose technologies (electrification, computerization) often advantage more educated and better trained workers (Goldin and Katz 2008).

Although new technologies alter the relative demand for labor by education and occupational skills, the impact of technological change on the wage structure also depends on changes in the supply of skills that are greatly affected by access to different education and training opportunities. The wage structure and educational wage differentials more broadly are shaped by supply factors (education and immigration), demand factors (technology and trade), and labor market institutions such as unions and minimum wage policies (Katz and Autor 1999). But a focus on the roles of the relative supply and demand for more-educated vs. less-educated workers through the framework of a *race between education and technology* (RBET) neatly illuminates long-run U.S. wage structure changes as shown by Katz and Murphy (1992), Goldin and Katz (2008), and Autor, Goldin, and Katz (2020). Technological change and educational advance also are the most important proximate factors in economic growth with rising educational attainment alone accounting for 45 percent of worldwide growth in income per capita since 1980 with about one-third of education's contribution to growth arising from skill-biased technical change increasing the returns to education (Gethin 2025).

In this talk, I will first put technological change, educational advance, and the wage structure into historical perspective using the RBET framework. I will examine the case of United States from the 19th century to the first part of the 21st century and update the evidence on U.S. wage structure changes and the RBET hypothesis from Autor, Goldin, and Katz (2020). I will then discuss emerging issues related to AI and remote work for understanding how technology is impacting and may continue to affect the labor market and education in the 21st century.

The RBET framework emphasizing secular growth in the demand for skill (the relative demand for more-educated workers) from skill-biased technical change combined with rapid, but time-varying, growth in the relative supply of more-educated workers from changes in access to education, for the most part, succinctly accounts for the long-run evolution of the U.S. wage structure from the 19th century to around 2015. The post-1980 rise in U.S. wage inequality combines strong growth in the demand for college educated workers from computerization (especially in the 1980s and 1990s) with a slowdown in the growth of the relative supply of more-educated workers relative to the mid-20th century (1940 to 1980). Rising education returns

can explain 75 percent of rising wage inequality for 1980 to 2000 but only 33 percent of the rise in U.S. wage inequality in the 21st century (2000 to 2023). The RBET empirical model of Goldin and Katz (2008) overpredicts that college wage premium in the 2020s failing to capture its stagnation since 2015, particularly in the post-pandemic period. The RBET framework remains relevant in the 21st century but needs to be modified to account for the bundling of tasks into occupations, rise of remote work and AI, and differences in the likely impacts on labor demand and the organization of work between traditional (classical) computing that largely can automate routine tasks and AI that can learn and potentially automate non-routine tasks.

I. Long-run Changes in the US Wage Structure and Educational Attainment

Figure 1 plots the evolution of U.S. educational/occupational wage differentials on as consistent a basis as possible from 1825 to 2023. Occupational wage gaps between clerical and production workers are based on civilian hires of the U.S. military for 1825 to 1875 from Katz and Margo (2014) and various series from Goldin and Katz (2008) for 1890 to 1959. The high school and college wage premium series for 1914 to 2023 combine data from the 1915 Iowa State Census, the first U.S. representative individual-level sample with labor market earnings and educational attainment, with U.S. Census and March Current Population Survey (CPS) micro-sample data for 1940 to 2024.

The historical long-term series on the clerical-production worker occupational wage differential implies a rising high school (educational) wage premium in the 19th and early 20th centuries. The shift from the artisanal shop to the factory and larger-scaled enterprises with water and steam power and eventually electricity increased the demand for more-educated workers in the face of modest supply growth given limited access to high school for most U.S. youth prior to 1910 or so. The rapid increase in the supply of high school educated workers from the grassroots U.S. high school movement starting around 1910 helped generate a large fall in the high school and white-collar wage premiums from 1910 to 1960 (Goldin and Katz 2008). The college wage premium narrowed through the two World Wars from 1914 to 1950, rebounded in the 1950s and 1960s, declined a bit with a large surge in the supply of college educated workers in the 1970s, increased from 1980 to 2000, continued rising through 2015, and has been flat since 2015. The information revolution from business machines to computerization and growing complexity of much knowledge has buoyed the demand for more-educated workers over the last century. The college wage premium today remains at a higher level than a century ago despite large increases in the educational attainment of the U.S. workforce and the relative supply of college workers.

Long-run U.S. educational advance is highlighted in Figure 2, providing the mean years of schooling at age 30 of each U.S. birth cohort born from 1876 to 1993. The rise of mass secondary schooling in the first half of the twentieth century and expansions in access to college in the mid-twentieth century yielded huge increases in educational attainment. Mean years of

completed schooling increased by 5.9 years (from 7.3 to 13.2 years), or by nearly 0.8 years per decade or close to 2 years per generation, for cohorts born from 1876 to 1951.

Educational attainment plateaued with the post-Vietnam War draft cohorts born starting in 1951 and has grown much more slowly than previously over the last for decades for the birth cohorts becoming prime age workers after 1980. Educational attainment at age 30 for the 1951 to 1993 birth cohorts rose by 1.13 years up to a level of 14.36 years, a rate of increase of 0.27 years per decade. The growth of U.S. college access after1980 increasingly shifted to lesser-resourced and less-selective public teaching-oriented institutions, community colleges, and for-profit colleges as compared to rapid expansion of access to high-quality high school in the first half of the 20th century and to relatively well-resourced public universities over much of the 20th century (Bleemer and Quincy 2025). Today's new prime age workers are the most educated cohorts in U.S. history but much less so relative to their parents than in the past. The consequence has been a sharp slowdown in the growth of the relative supply of more-educated to less-educated U.S. workers since 1980 that plays an important role in the post-1980 rise in the U.S. college wage premium and overall wage inequality.

II. The Race between Education and Technology, 1914 to 2023

Following Katz and Murphy (1992), Goldin and Katz (2008), and Autor, Goldin, and Katz (2020), I model changes in the college wage premium from 1914 to 2023 as arising from a race between the supply of skills (driven by changes in the educational attainment of the work force) and the demand for skills (driven by skill-biased technological change).

I use what has become known as the canonical model of the RBET by postulating a simple CES production function for aggregate output *Q* with two factors, "skilled" workers (S) and "unskilled" workers (U), who perform imperfectly substitutable tasks:

$$Q_t = [\alpha_t(a_t L_{S_t})^{\rho} + (1-\alpha_t)(b_t L_{U_t})^{\rho}]^{\frac{1}{\rho}} \quad (1)$$

where L_{S_t} and L_{U_t} are the quantities of skilled labor and unskilled labor employed in period *t*, a_t and b_t represent skilled and unskilled labor augmenting technological change, and α_t is a time-varying technology parameter indexing the share of work activities allocated to skilled labor. The parameter ρ is related to σ_{SU}, the aggregate elasticity of substitution between skilled and unskilled labor, with $\sigma_{SU} = \frac{1}{1-\rho}$. Skill-biased technical change arises from increases in (a_t/b_t) or in α_t. One can interpret an increase in (a_t/b_t) as *intensive* skill-biased technological change in which skilled workers get relatively better at their jobs; and increases in α_t as *extensive* skill-biased technical change that shifts work tasks from unskilled to skilled workers such as could arise from higher rates of task replacement by automation for unskilled than for skilled workers. Since I focus on the college and high school divide, I define skilled workers (S) as "college equivalents" (college graduates plus half of those with some college) and unskilled workers (U)

as "high school equivalents" (those with 12 or fewer years of schooling and half of those with some college).

A reduced-form formulation along the lines of equation (1) with both intensive and extensive margins of technological change can be micro-founded through task-based models of technical change along the lines of Autor, Levy, and Murnane (2003) and Acemoglu and Restrepo (2019, 2022). Automation technologies in which capital (or software) is enabled to replace workers in certain tasks that disproportionately displace less-skilled workers can be interpreted as an increase in α_t in equation (1). Rapid labor augmenting (intensive margin) skill-biased technical change from an increase in the growth rate of a_t and (a_t/b_t) is associated with rapid productivity growth. But "so-so" technologies that make it only marginally cost effective for firms to substitute capital for less-skilled workers (increasing α_t) and are not fundamental enough to lead to large productivity increases fostering the creation of new tasks (such as some forms of automated customer service) potentially can have large impacts in increasing wage inequality (skill differentials) and reducing labor's share without much impact on productivity growth (Acemoglu and Restrepo 2019). Thus, the impact of skill-biased technical change on wage inequality is not necessarily related to the rate of aggregate productivity growth.

Assuming workers are paid their marginal products, I can use equation (1) to solve for the ratio of the marginal products of the two skill groups yielding a relationship between relative wages and relative factor supplies:

$$ln\left(\frac{w_{S_t}}{w_{U_t}}\right) = \frac{1}{\sigma_{SU}}\left[D_t - ln\left(\frac{L_{S_t}}{L_{U_t}}\right)\right] \qquad (2)$$

where D_t, measured in log quantity units, depends on the skill-biased technological change parameters and indexes relative demand shifts favoring college equivalents. Equation (2) illustrates how the evolution of the college wage premium depends on a race between technology (the relative demand for skills) and education (the relative supply of skills). The aggregate elasticity of substitution between college and high school equivalents (σ_{SU}), depending on both production function technical substitution possibilities and on consumer substitution, determines the quantitative impact of changes in skill supplies on the college wage premium. The RBET formulation in equations (1) and (2) can also be extended to allow for imperfect competition in the labor market with differential monopsony power for more-educated vs. less-educated workers and to incorporate labor market institutions such as minimum wage policies (Card et al. 2018; Haanwinckel 2025; and Vogel 2025).

I next examine the importance of supply and demand shifts for the long-run evolution of the college wage premium displayed Figure 1. I estimate a version of equation (2) for the U.S. college wage premium regressed on the relative supply of college equivalents to high school equivalents for 1914 to 2023 with demand shifts approximated by smooth time trends and, in some specifications, an allowance for World War II institutional wage-setting pressures in the

1940s. Table 1 presents the estimates that update with data through 2023 and uses the same (now pre-specified) specifications estimated by Goldin and Katz (2008) through 2005.

The main findings are of a large positive secular trend in the relative demand for college workers and a substantial negative impact of increases in the relative supply of college workers on the college wage premium. A 10 percent increase in the relative supply of college equivalents typically reduces the college wage premium by around 6 to 6.5 percent. The implication is that σ_{SU} is approximately 1.59 (using the estimate in col. 2 of Table 1), consistent with other estimates in the literature, typically in the 1 to 2 range after conditioning on time trends (Katz and Autor 1999). Figure 3 plots the actual college wage premium and the predicted college wage premium using the estimates from col. 2 of Table 1.

Figure 3 reveals that a model with smooth secular relative demand trends favoring college workers, together with fluctuations in relative supply growth, does a reasonable job of capturing the long-term evolution of the college wage premium at least through 2015. There are exceptions where other factors seem crucial such as the degree wage compression in the 1940s (with rising union strength, extremely tight labor markets, and government wage pressures) and the late 1970s (with high inflation and indexed union wage contracts for blue collar workers and a federal minimum wage increases). The estimates also imply some acceleration in the trend relative demand growth for college workers in the post-World War II period and a somewhat puzzling slowdown starting in the early 1990s. The impact of computers on labor demand is likely not well-approximated by a two-skill group model with much evidence indicating middle-skill jobs (clerical and production jobs specialized in "routine" tasks) being most susceptible to displacement from traditional computerization (Autor, Levy, and Murnane 2003; Autor, Katz, and Kearney 2008). And Vogel (2025) shows that an extension of canonical RBET model of equation (2) to account for institutions through the addition of the effective real minimum wage largely eliminates the implied slowing of skill-biased technical change (relative demand growth) after 1992 when estimated through 2016.

Figure 3 further shows that the simple RBET model fails to predict the flattening of the college wage premium after 2015 and particularly overpredicts it in the post-pandemic period (2021 to 2023). A potential factor is the sharp rise in the share of individuals working from home after the Covid-19 pandemic with the increase being much larger for more-educated workers (Barrero, Bloom, and Davis 2023). Remote work options are highly valued amenities for many workers (Cullen, Pakzad-Hurson and Perez-Truglia 2025; Mas and Pallais 2017) and could have lessened real wage growth pressure disproportionately for college educated workers. In fact, Afrouzi et al. (2025) find that U.S. occupational real wages declined the most from 2021 to 2023 in high-wage occupations amenable to work from home. Tight labor markets (Autor, Dube, and McGrew) and greater upward job mobility prospects for low-wage workers in the late 2010s and from 2021 to 2024, a temporary surge in inflation combined with nominal wage rigidity in the post-Covid period (Afrouzi et al. 2025), and initial impacts of AI in reducing demand for

younger college workers (Brynjolfsson, Chandar, and Chen 2025) are other possible contributors to a more compressed than RBET predicted college wage advantage over the last decade.

Table 2 uses the estimates from col. (2) of Table 1 to summarize the contributions of changes in the relative supply and implied relative demand for college equivalents to changes in the college wage premium over different sub-periods for 1914 to 2023. The large rise in the college wage premium since 1980 is driven more by a slowdown in relative supply growth rather than by an acceleration in skill-biased technological change (or some other source of relative demand growth) as can be seen in a comparison of the 1979 to 2023 period of a rising premium to the 1939-79 period of a falling premium. The log college wage premium increased by 0.261 from 1979 to 2023 (from 0.4 to 0.661 or by 0.059 per decade) but *declined* by 0.088 (by 0.022 per decade) during the mid-20th century from 1939 to 1979. The rate of growth of the log relative supply of college equivalents was 0.307 per decade (or 3.07 percent per annum) from 1939 to 1979. But it decreased to 0.208 per decade (2.08 percent per annum) from 1979 to 2023.

The slowdown in relative supply growth accounts for 77 percent (0.062) of the 0.081 per decade increase in the growth rate of the college wage premium post-1979 relative to 1939 to 1979, under the assumption that σ_{SU} = 1.59 based on the estimate from col. (2) of Table 1. The implied acceleration in the growth of log relative demand for college equivalents of 0.030 per decade explains 23 percent (0.019) of the surge in the college wage premium after 1979, as compared to the modest decline from 1939 to 1979. Table 2 also indicates that the stagnation of the growth of the college wage premium in the 21st century (1999 to 2023) is entirely driven by a deceleration in skill-biased technical change as compared to the late 20th century (1979 to 1999). This implied slowdown in the growth of relative demand for college equivalents in 1999 to 2023 vs. 1979 to 1999 could partially reflect omitted institutional factors rather than entirely being driven by slower skill-biased technical change. The sharp decline in unions and the real minimum wage in the 1980s and 1990s as compared to a rise in the effective real minimum wage from aggressive state minimum wage increases in the 2010s could play a key role as seen in Vogel's (2025) analysis of the college wage premium from 1963 to 2016 incorporating supply, demand, and institutional (minimum wage) changes.

But much evidence indicates that the secular time trend terms in the estimated version of equation (2) substantially represent skill-biased technical change. Indirect evidence includes large within-industry and within-firm shifts increasing the relative utilization of college workers in the face of rising educational wage differentials in recent decades (and in the 1950s and 1960s) strongly suggesting skill-biased technical change (Katz and Murphy 1992; Katz and Autor 1999). Case studies document that the adoption of new technologies has led to increased relative employment of more-educated workers in multiple sectors including financial services, auto repair, valve manufacturing, and steel (e.g., Autor, Levy, and Murnane 2002; Bartel, Ichniowski, and Shaw 2007). Observational studies find strong indictors of technology-skill complementarity including positive relationships between indicators for more advanced

technologies (computer investments, R&D, new equipment investments) and work force skill measures (education, occupation, tasks) in levels, changes, and acceleration (e.g., Doms, Dunne, and Troske 1997; Autor, Katz, and Krueger 1998). Quasi-experimental studies show that increased access to broadband (Akerman, Gaarder, and Mogstad 2015), tax incentives to invest in information technology (Gaggle and Wright 2017), greater industrial robot exposure (Acemoglu and Restrepo 2020), and differential exposure to automation-based routine-task displacement shocks (Acemoglu and Restrepo 2022) have shifted the skill mix toward more-educated workers and increased their relative earnings.

I next examine how much of the overall rise in U.S. wage inequality since 1980 can be accounted for by increased educational wage differentials and how the patterns differ in the late 20th century vs. the early 21st century. I follow the approach of Goldin and Katz (2007) and update to 2023 the estimates through 2017 presented in Autor, Goldin, and Katz (2020). I use data spanning 1979 to 2024 from the CPS Merged Outgoing Rotation Groups (MORG). Mincerian cross-section human capital earnings functions for log hourly wages modified to allow the "returns" to an additional year of schooling to differ for K-12, college, and post-BA schooling are estimated for 1980 (1979 to 1981 pooled), 2000 (1999 to 2001), and 2023 (2022 to 2024).

I examine the role of changing education returns from 1980 to 2000 by first imposing the estimated 2000 returns to schooling in 1980 to create adjusted individual wages holding everything else constant. I then compare the distributions of actual and adjusted wages in 1980 to determine what wage inequality would have been in 1980 with education returns at 2000 levels. Wages in 2000 are analogously adjusted by imposing the 1980 education returns. The average of the results of the two simulations is then used. I repeat this approach for 2000 to 2023. The education return contribution for 1980 to 2023 is the sum of the 1980 to 2000 and the 2000 to 2023 education return contributions. The earnings regressions and simulations are presented in Table 3. Wage inequality as measured by either the variance of log(wages) or the 90-10 log wage differential rose by substantially more from 1980 to 2000 than from 2000 to 2023.

The estimates of the earnings regressions show the returns to post-secondary education increased and convexified from 1980 to 2000 to 2023 with the largest increase for post-BA (graduate and professional) schooling. The returns to a year of college rose sharply in the 1980s and 1990s (from 0.077 in 1980 to 0.126 in 2000) but show little change in the 2000s. The returns to a year of post-college also greatly increased from 1980 to 2000 and then continued to rise although more moderately after 2000 leading to a more than doubling from 0.067 in 1980 to 0.167 in 2023. Returns to K-12 schooling (driven by the high school wage premium) rose from 1980 to 2000 before declining substantially from 2000 to 2023 to a lower level than in 1980 with fast mean real wage growth for workers with less than a high school degree over the past decade.

Increased returns to schooling driven by the rise in returns to post-secondary education account for most of the increase in wage inequality (54 percent of growth in the variance of log hourly wages and 62 percent of the rise of 90-10 log hourly wage ratio) for the full 1980 to 2023 period. The large rise in education returns in the 1980s and 1990s can explain 75 percent (0.048) of the 0.065 increase in the variance of log hourly wages from 1980 to 2000. The more modest rise of education returns since 2000 accounts for 33 percent (0.011) of the smaller (0.033) increase in the variance of log hourly wages from 2000 to 2023.

The two-skill RBET model can account for the vast majority of the enormous increase in wage inequality from 1980 to 2000, when a substantial slowdown in the growth of the relative supply of college workers and some acceleration in the impacts of skill-biased technological change on the relative demand for college workers produced a large rise in the college wage premium. But most the (more modest) rise in wage inequality since 2000 has occurred within, rather than between, education group with an especially rapid rise in inequality among college graduates, a continued steady increase in the 90-50 wage ratio and top-end inequality, and a decline in the 50-10 wage ratio.

III. Artificial Intelligence, Education, and the Labor Market in the 21st Century

Traditional computers (classical computing) required explicit and detailed instructions for how to transform inputs (data) into outputs: when software engineers wrote code to perform a task, they were codifying that task. Task-based models (starting with Autor, Levy, and Murnane 2003) are well-suited to understanding the impacts of the advances in classical digital computing on the labor market from the mid-20th century to the early 2010s. The task framework conceptualizes the process of accomplishing a job as a series of tasks that can be done either by workers or by machines. Classical computerization facilitated the shifting of many routine cognitive and manual human tasks to machines especially for middle-wage (middle-skill) clerical and production jobs. It proved far more difficult to program computers to accomplish tasks requiring tacit knowledge including the more abstract and non-routine tasks of high-level professionals and mangers (depending on expert judgement, creativity, and interpersonal skills) as well as the non-routine manual tasks of workers doing in-person services from janitorial to care work or on-site construction jobs. Traditional computerization complemented more educated workers in professional and managerial positions by making key inputs into their decision-making jobs (such as information access, data, and basic analysis and calculations) less expensive and more productive. And such computerization had little direct impact on the demand for non-routine manual workers in lower-wage and construction jobs. Rapid classical computing advances contributed to labor market polarization reducing demand for routine middle-skill (production, office/clerical, and sales) jobs relative to high-education (professional and managerial) jobs and non-routine manual (in-person service, operator/laborer) jobs as seen in occupational employment growth patterns, rising upper tail wage inequality, and flat or declining

lower-tail wage inequality from the 1980s to the mid-2010s (Autor, Katz, and Kearney 2006; Autor 2022).

Tasks involving tacit knowledge proved resistant to classical computerization since the explicit steps to accomplishing these tasks (identifying a cat video, motivating an employee) are not formally known and may not be able to be clearly communicated even by individuals performing such tasks beyond providing examples. Machine learning and AI overcome such constraints by inferring instructions and tacit relationships by training on a large enough number of examples (big data). AI can learn to do tasks (writing emails, identifying cat videos, making presentations, analyzing data) even when no formal instructions are provided and has the potential to automate many non-routine cognitive and manual tasks (National Academies of Sciences, Engineering, and Medicine 2025).

AI is a general-purpose technology that has undergone significant recent progress that is likely to continue given massive private and public investments to build bigger and better models. AI investments and adoption by employers started have started impacting labor demand in many sectors over the past decade. ChatGPT's introduction in November 2022 accelerated the process by providing widespread public and workforce access to generative AI through LLMs. Bick, Blandin and Deming (2025) find in late 2024 that 23 percent of U.S. employed residents used generative AI at work in the past week and 9 percent used it every day at work; generative AI work users report a mean time savings of 5.4 percent implying a1.4 percent time savings among all workers (including non-users) from generative AI usage. Hartley et al. (2025) report that the share of the share of U.S. labor force using generative AI at work had increased to 46 percent by July 2025.

The impacts of advances in AI on productivity and on labor markets remain highly uncertain and are just beginning to be observed and assessed. AI is likely to alter the nature of many jobs as AI automates certain routine and non-routine human tasks, as AI tools serve as collaborators augmenting the productivity of workers in their remaining human tasks, and as AI advances spur new products, new services, and new work. AI's labor market impacts will depend on how it alters the demand for different types of worker expertise, how tasks are bundled into jobs and occupations, and the extent to which AI automation disproportionately impacts the more-skilled vs. less-skilled tasks in a job. Hampole et al. (2025) examine worker task-level exposure to AI and machine learning technologies from 2010 to 2023. They find reduced labor demand for occupations with high exposure across many tasks, increases in employment in occupations with concentrated exposure in a small set of tasks allowing workers to shift effort to non-displaced tasks, and productivity-driven employment increases across all occupations at AI-adopting firms. Autor and Thompson (2025) find how task automation impacts on occupational wages depends on whether automated tasks are those requiring relatively low expertise thereby raising average expertise and wages in the occupation (e.g., accounting clerks) vs. automating the higher expertise tasks, lowering average expertise, and wages (e.g., stock and inventory

clerks). Freund and Mann (2025) postulate that AI automation may have heterogeneous effects on workers in exposed occupations tending to displace workers specializing in information processing tasks and helping workers in more customer-facing and coordination tasks.

The early evidence on the impacts of generative AI diffusion on exposed workers is mixed. Humlum and Vestergaard (2025) for Denmark using survey data on LLM usage find little impact yet on wages and hours worked. Eckhardt and Goldschlag (2025) using multiple measures of occupational AI exposure for the United States observe no evidence so far of employment or unemployment impacts since the release of ChatGPT. Johnston and Makridis (2025) report some evidence of faster wage and employment growth after ChatGPT in sectors with greater LLM productivity augmentation exposure with possible negative effects for sectors with more LLM substitution exposure.

Well-designed experimental and quasi-experimental studies find the adoption of generative AI increases worker productivity in professional writing tasks (Noy and Zhang 2023), customer support (Brynjolfsson, Li, and Raymond 2025), software development (Cui et al. 2025), and taxi driving (Kanazawa et al. 2022) with larger gains typically for novice and less skilled workers in the occupation. In contrast, Brynjolfsson, Chandar and Chen (2025) using payroll data from ADP report a decline in employment for younger, less experienced workers in more AI exposed occupations and expansion of employment for more experienced workers in such occupations since more widespread adoption of generative AI. Hosseini and Lichtinger (2025) similarly find a decline of employment and hiring of junior (entry-level) workers and rise in employment of more experienced workers following employer AI adoption using Revelio Labs LinkedIn data. And the unemployment rate for young college workers has been unusually high relative to other workers the last several years in the post-pandemic labor market.

The decline in entry-level jobs and expansion of employment of more experienced workers in AI-exposed occupations and firms suggests that AI may substitute (automate) entry-level work (possibly learning from the same educational written materials as high school and college students) but complement more experienced workers with greater tacit knowledge and expertise not easily available from existing AI training data bases. On the other hand, experimental studies indicate AI tends to most benefit entry-level workers who then can more quickly can mimic the strategies of more experienced and successful workers. A possible reconciliation comes from the insightful model of Ide and Talamás (2025) who introduce AI agents, who can act either autonomously (as co-workers) or non-autonomously (as co-pilots), into a knowledge hierarchy framework where less knowledgeable workers (and novices) do more routine (and entry-level) work and more knowledgeable (more senior) workers act as managers/supervisors dealing with exceptions and helping junior workers with harder assignments. Autonomous AI agents can substitute for less knowledgeable, entry-level work and benefit more knowledgeable and experienced workers who are freed from helping junior workers and from more mundane tasks. Non-autonomous generative AI agents serving as co-pilots (as in

the studies of customer service workers and software developers) benefit less knowledgeable novice workers and may substitute for middle managers. The impacts of AI on employment opportunities for different workers likely will depend on the mix of tasks in a job, the types of tasks automated by AI, and the extent to which AI tools can act as collaborators helping less experienced workers as opposed to mainly augmenting more senior and knowledgeable workers.

AI advances permitting more senior workers to complete more tasks independently without needing assistance ("grunt work") from less knowledgeable and novice workers may reduce entry-level job opportunities and the extent of informal mentoring of junior workers. The consequence could be reduced intergenerational transmission of tacit knowledge necessary for productivity gains and for the career advancement of younger workers (Ide 2025). The rise of remote work and its popularity among many senior workers seems to be creating further barriers to mentoring and career growth opportunities for entry-level workers. In fact, Emanuel, Harrington, and Pallais (2025) find that unemployment for young workers (recent graduates) remains most elevated in the post-pandemic period (2022-24) for those in more remoteable occupations.

AI acting as a collaborative co-pilot might increase the demand for "translational" expertise whereby less experienced or middle-skilled workers combine subject area knowledge with inputs and guidance from AI to carry out more advanced work assignments such as health aides doing tasks previously requiring nurses or nurse practitioners doing tasks previously requiring medical doctors (National Academies of Sciences, Engineering, and Medicine 2025). Education and training may need to change to accommodate an increased demand for translational expertise as well as to provide new graduates with more experiential workplace learning to be prepared for future entry-level work. Such a shift might involve more of an emphasis towards strong basic skills (numeracy and literacy) and social/communication skills, foundational training in specific subject expertise (e.g., accounting, medicine, plumbing), and serious experiential learning opportunities combining the strengths of post-secondary vocational training and a liberal arts education. A cooperative education model for higher education, such as the one used at Northeastern University, alternating semesters of academic study with full-time work to gain hands-on learning is a promising approach that might be considered to expand post-secondary education opportunities in the emerging AI era. Sectoral employment training programs and registered apprenticeship programs providing occupational and soft-skills training and wraparound services with strong connections to employers in growing sectors represent another promising training model. Recent randomized evaluations show that sectoral employment programs providing training, internships, and support service lasting from several months to two years have generated substantial and persistent earnings increases of 20 to 35 percent (Katz et al. 2022). AI itself also has the potential to improve the delivery of mass education using big data to provide personalized learning opportunities, enhance learning salience, and teach at the right level.

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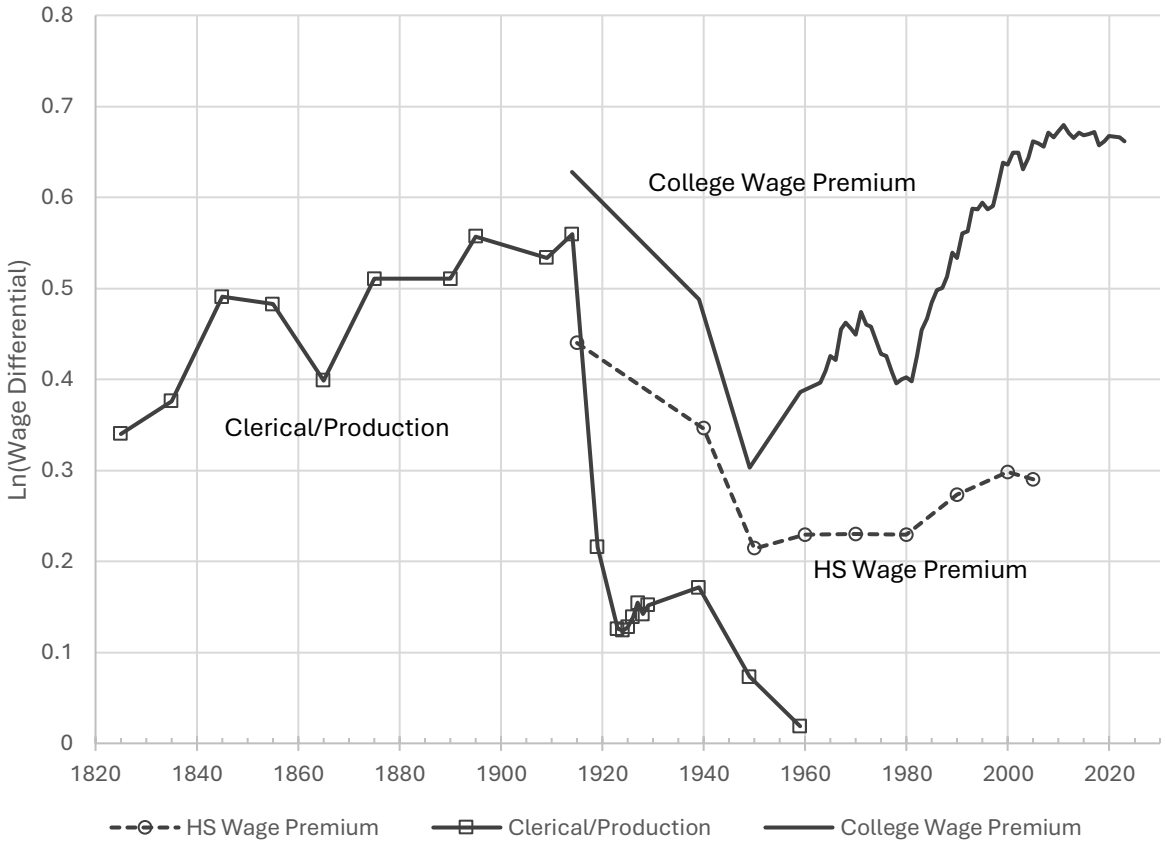
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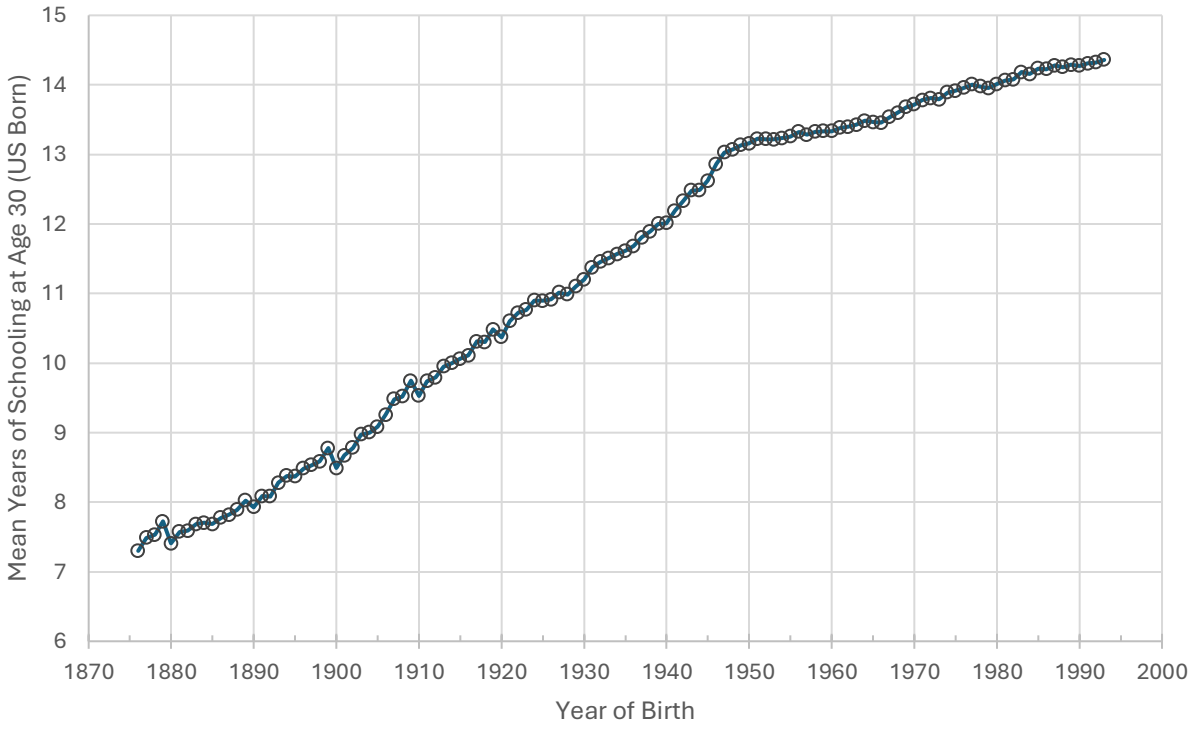
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Figure 1: Educational and Occupational Wage Differentials: 1825 to 2023



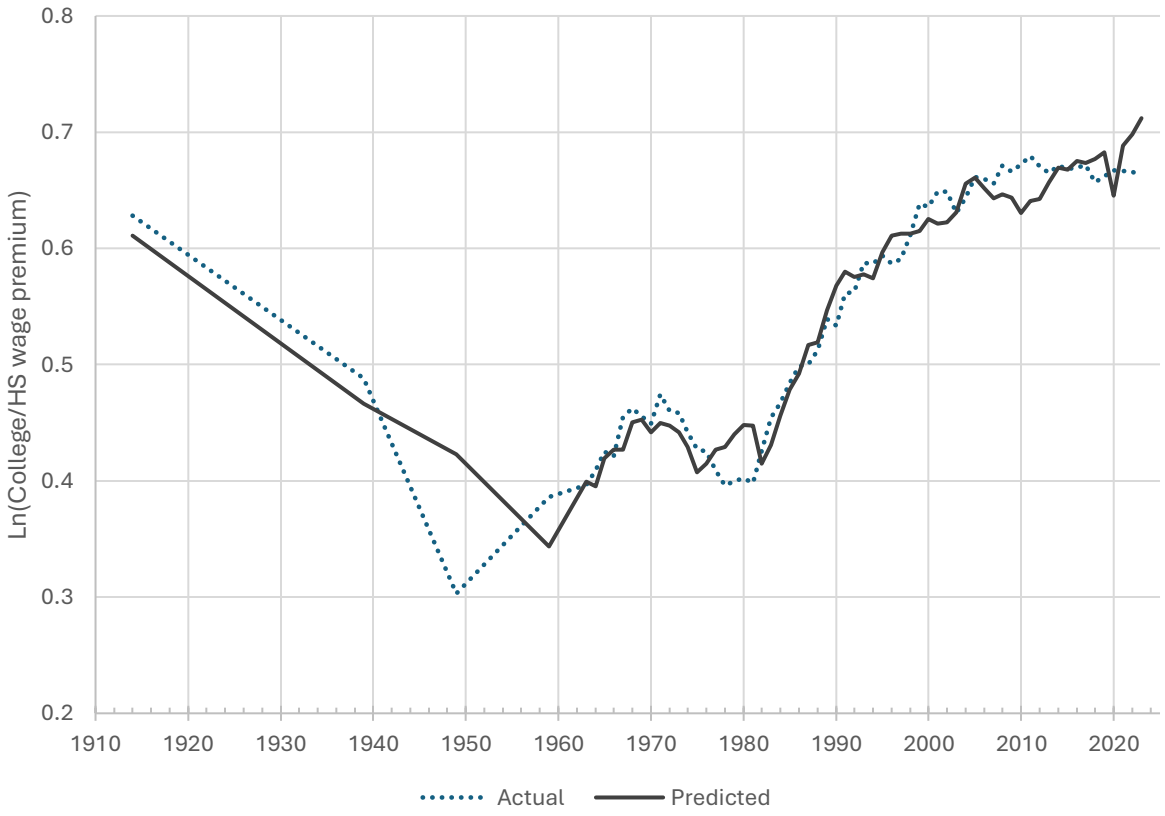
Sources and Notes: Clerical/production worker series for 1825 to 1875 is based on Katz and Margo (2014, table 1.5), and that for 1890 to 1959 is from Goldin and Katz (2008, table 2.2). High school wage premium series is from Goldin and Katz (2008, table D.1). College wage premium series from Goldin and Katz (2008, table 8.2) updated to 2023. See the online appendix for details to Autor, Goldin, and Katz (2023) for details.

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



Sources and Notes: US Census IPUMS data from 1940 to 2000 and CPS MORG data from 2005 to 2024. The figure updates Goldin and Katz (2007, figure 7) and Autor, Goldin, and Katz (2020, figure 2). See the online appendix to Autor, Goldin, and Katz (2020) for details.

Figure 3: Actual vs. Predicted College Wage Premium, 1914 to 2023



Source and Notes: The actual college wage premium is the series plotted in Figure 1. The predicted college wage premium series plots the predicted values for the college wage premium from the regression in col. (2) of Table 1.

Table 1: Determinants of the College Wage Premium: 1914 to 2023

	(1)	(2)	(3)	(4)
(College/high school) supply	-0.608	-0.629	-0.650	-0.665
	(0.070)	(0.076)	(0.062)	(0.078)
(College/high school) supply × post-1949				0.0148
				(0.0470)
Time	0.00492	0.0104	0.0108	0.0115
	(0.00191)	(0.00206)	(0.00167)	(0.00290)
Time × post-1949	0.0203			
	(0.00120)			
Time × post-1959		0.0165	0.0164	0.0157
		(0.0010)	(0.00083)	(0.00246)
Time × post-1992	-0.00909	-0.0109	-0.00106	-0.0106
	(0.00124)	(0.00138)	(0.00111)	(0.00113)
1949 Dummy			-0.134	-0.144
			(0.0233)	(0.0402)
Constant	-0.624	-0.713	-0.738	-0.772
	(0.154)	(0.163)	(0.132)	(0.171)
R^2	0.945	0.940	0.961	0.962
Number of observations	65	65	65	65

Sources and Notes: Updates Table A1 of Autor, Goldin, and Katz (2020) to 2023. Each column is an OLS regression of the college wage premium on the indicated variables using a sample covering the years 1914, 1939, 1949, 1959, and 1963 to 2023.

Standard errors are given in parentheses below the coefficients. The college wage premium is a fixed weighted average of the estimated college (exactly 16 years of schooling) and post-college (17+ years of schooling) wage differential relative to high school graduates (those with exactly 12 years of schooling). (College/high school) supply is the log supply of college equivalents to high school equivalents both measured in efficiency units. "Time" is measured as years since 1914. The samples used include workers from 16 to 64 years old. The data for 1963 to 2017 are from the 1964 to 2024 March CPS samples. The college wage premium and relative supplies in efficiency units for 1963 to 2023 use the same data processing steps and sample selection rules as those described in the data appendix to Autor, Katz, and Kearney (2008). The college wage premium series is the same as plotted in Figure 1. The 2018 to 2019 change in log relative supply is from the CPS MORG data to prevent pandemic related disturbances response rate in the March 2020 CPS from impacting the pre-pandemic period. Further details can be found in the online appendix to Autor, Goldin, and Katz (2020).

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

	Changes in the Relative Wage	Changes in Relative Supply	Changes in Relative Demand (σ_{SU} = 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

Sources: The underlying data are from the 1915 Iowa State Census, 1940 to 1970 Census IPUMS, and 1964 to 2024 March CPS.

Notes: Updates Table A2 of Autor, Goldin, and Katz (2020) to 2023 using same methodology. The "relative wage" is the log (college/high school) wage differential, which is the college wage premium. The underlying college wage premium series is plotted in Figure 1. The relative supply and demand measures are for college "equivalents" (college graduates plus half of those with some college) relative to high school "equivalents" (those with 12 or fewer years of schooling and half of those with some college). Relative skill supplies are measured in efficiency units and are the same series used for the regressions in Table 1. The log relative demand measure (D_t) is based on equation (2) in Autor, Goldin, and Katz (2020) and is given by $D_t = \ln(L_{S_t}/L_{U_t}) + \sigma_{SU} \ln(w_{S_t}/w_{U_t})$, under the assumption that σ_{SU} = 1.59 based on the estimate from col. (2) of Table 1.

Table 3: 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	1.495	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

Sources and Notes: CPS MORG files for 1979 to 1981, 1999 to 2001, and 2022 to 2024. The samples include wage and salary workers aged 18 to 64 years with 0 to 39 years of potential experience using the data processing methods for the CPS May/MORG samples described in the appendix to Autor, Katz, and Kearney (2008). 1980 pools the 1979 to 1981 samples; 2000 pools the 1999 to 2001 samples; 2023 pools the 2022 to 2024 samples. Var ln(w) is the variance of the log hourly wage. 90-10 is the log 90-10 wage ratio. Education returns are estimated for each period from human capital earnings regressions with the log hourly wage as the dependent variable run on a linear spline in years of schooling with break points after 12 and 16 years of schooling; a quartic in experience; race, region, and gender dummies; year dummies; and interactions of gender and the experience quartic. This table updates Table A.3 of Autor, Goldin, and Katz (2020) to 2023 as opposed to 2017.

I examine the role of changing education returns from 1980 to 2000 by first imposing the 2000 returns to schooling in 1980, thereby adjusting individual wages in 1980. I then compare the distributions of actual and adjusted wages in 1980 to determine what wage inequality would have been with education returns at 2000 levels examining the implied change in the Var ln(w) and 90-10. I adjust 1980 wages to incorporate 2000 education returns by adding to an individual's wage in 1980 the sum of the product of that individual's years of schooling in each category and the difference between the estimated returns to schooling in 2000 and 1980 for that schooling category. Wages in 2000 are analogously adjusted by imposing the 1980 education returns. The average of the results of the two simulations the change in Var ln(w) and 90-10 is then used for the education return contribution. I repeat this approach for 2000 to 2023. The education return contribution for 1980 to 2023 is then the sum of the 1980 to 2000 and the 2000 to 2023 education return contributions for Var ln(w) and 90-10 respectively.