AI and the Future of Work in an Aging Economy

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July 7, 2025

PRC WP2025-14
Pension Research Council Working Paper
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Abstract

We examine the potential disruptions and opportunities for older workers from Artificial Intelligence (AI). Older workers' labor market experience is marked by lower fluidity across occupations, sectors, and jobs, suggesting ex ante limited capacity to adjust to AI-driven structural transformation. Yet, a larger share of older workers, compared to younger peers, is already employed in occupations expected to benefit from AI as a complementary technology. Conditional on acquiring the required skills, these workers could enjoy growing opportunities and higher wages. Some features of these jobs, such as the ability to telework, align with senior workers' preferences and may incentivize greater employment at older ages.

Keywords: Aging, Older Workers, Retirement, Artificial Intelligence, Structural Transformation

JEL Codes: J11, J14, J24, J26, O33

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The rapid development of Artificial Intelligence (AI) and its fast adoption across a vast range of industries has spurred a vibrant debate over its possible impact on the labor market. At the same time, in the US, as in other advanced economies, the secular trend of population aging prompts additional questions on the implications of AI for older workers. Could AI-based technologies create opportunities and incentives for older workers to extend their careers? Or will they bring about employment disruptions that would make navigating the late stages of their careers more challenging? Whether AI-driven economic growth ultimately translates into widespread improvements in living standards depends heavily on how the labor force, and in particular its more vulnerable members, adjust to the structural transformation it induces. It is therefore crucial for all stakeholders, including policymakers, employers, unions, and the education sector, to identify both rising challenges and opportunities for older workers, with a view towards increasing their resilience to possible shocks and encouraging longer working lives to mitigate aging-related macroeconomic challenges.

In this chapter, we provide descriptive analysis to guide this forward-looking discussion and inform policies to support older workers through AI-driven structural transformation. We first present standard indicators of labor market ‘fluidity,’ showing that older workers tend to be less resilient in response to job loss and are less prone to moving across sectors and occupations. We then use a classification of occupations’ likely exposure to the positive and negative effects of AI to examine how the employment composition of the current cohort of older workers compare to that of their younger peers. Using the adoption of robots and computers that led to automation from the last part of the 20th century until the 2010’s as a historical case study, we also discuss the implications of structural change for younger cohorts of older workers by the time they will reach the late-career stage. Additionally, we consider the age-friendly features of AI-complementary jobs, , as well as a set of other indirect channels, which may affect workers' decisions regarding the timing of retirement.

Structural transformation in the context of an aging economy

The application of technologies that fall under the definition of AI has been underway at a fast pace since the early 2010's (see for instance Bonfiglioli et al. 2025 and Agrawal et al. 2019). Nevertheless, AI received widespread and sustained only after the public release of OpenAI's large language model ChatGPT in October 2022, along with similar models by other developers in the following months. These models fall under the umbrella of Generative-AI technologies, which uses predictive algorithms not just to forecast outcomes, but to synthesize entirely new content in the form of text, images, and videos based on user-provided prompts and information inputs. Their release made the capabilities of AI technologies evident to the non-expert public, suggesting both scope for everyday use in a broad range of situations and the potential for significant disruptions to the current structure of the economy over the coming years, with first-order implications for the labor market.

While AI's full capabilities are yet to be known and its full scope for application remains uncertain, historical episodes of major technological advancements—most recently routine-biased automation and digitalization—have shown that the ensuing structural transformation of the economy entails significant reallocation of workers across sectors and occupations. Some jobs and skills may become sought-after while others may experience declining demand, so the inherent frictions of the labor market and workers' limited ability to adjust could ultimately create winners and losers. A fast-growing number of studies has therefore gathered early empirical evidence on the impact of AI on the labor market, considering firms' shifting demand for different occupations and skills (e.g., Bonfiglioli et al. 2025; Acemoglu et al., 2022a; Huang 2024), and the impact on labor productivity in narrowly defined jobs and industries.[1] Older workers particularly stand out as a potentially vulnerable group, as they tend to have more limited resilience to adverse shocks (Chan and Stevens 1999) and historically have been more negatively affected by automation and digitalization (e.g., Hendrick 1984; Casas and Román 2023; Yashiro et al. 2022).

In industrialized economies like the US, this discussion is taking place at a time of renewed interest in the changing nature of work, driven by the looming challenges brought about by an aging population. A confluence of demographic trends is putting the current social structure, with its organization around the 'three-stage' life-cycle, under stress, with a particular challenge for both publicly and privately funded pension and healthcare systems. The ongoing retirement of the large Baby Boomer generation with its long life expectancy, together with shrinking younger cohorts as a result of lower fertility rates, have driven the old-age dependency ratio from 19 percent in 1990 to 25 percent in 2020, and with a projected ratio of 36 percent by 2050.[2] This development implies a particular strain for publicly funded healthcare systems and old-age social security schemes—especially under pay-as-you-go structures whereby current pension benefits are financed through current workers' contributions. Yet, increased longevity also raises challenges for private and individual-centered pension schemes. In such systems, a longer life expectancy requires workers to set aside a larger share of their earnings or extend their careers to secure pension assets sufficient to sustain their desired living standards after retirement. At the macroeconomic level, this challenge may be exacerbated by general equilibrium effects, as the economy's neutral interest rate tends to fall with an aging population (Cacciatore et al. 2024), lowering the returns from savings and reducing workers' ability to fund their future consumption by compounding their wealth over time.

Amidst these challenges, extending working lives appears as an almost inevitable scenario to adjust to this demographic transition without significantly cutting the living standards of the elderly. Working until older ages would allow individuals to accumulate more savings to finance their retirement, while also contributing positively to output growth through their labor and to public finances via taxes. This choice may come at high personal costs, however, as it involves delaying leisure and incurring the risks of work-related health problems which become more frequent at older ages. In fact, as shown by a large literature (e.g., Rogerson and Wallenius 2022), working and retirement timing decisions are not solely dictated by statutory pensionable ages and financial considerations, but also by health, family situations, job satisfaction, the ability to adapt working arrangements to a changing lifestyle, and other personal factors. Moreover, the transition out of a career and into retirement need not to be an abrupt one and may involve a gradual reduction in the time spent working.

With these concerns in mind, the advent of AI spurs natural questions regarding whether the structural change brought about by the new technology could exacerbate the aging-related challenges or provide solutions (Alcover et al. 2021; Komp-Leukkunen 2023). AI may induce a reduction in the demand for positions held by older workers, which would in turn lead to a wave of early retirements and lower their prospects for an enjoyable old-age life. Alternatively, it may entail a rise in demand for labor, changing the tasks performed at work, in a way that may encourage longer careers and postponing retirement. The extent to which either of these shifts may take place also depends on whether older workers possess the skills needed to operate AI and integrate it into their key activities. If not, their ability to acquire that knowledge or to transition to industries and occupations where it is less required will be a key determinant of their ability to adjust to these shifts. Finally, technological change could alter the professional trajectories of workers who are not yet old and, in turn, affect the late stages of their careers in ways that are difficult to foresee at this stage.

It is too early to provide answers with a strong degree of confidence, as AI is still far from its likely potential and its full effects on the labor market are yet to unfold. Nevertheless, in this chapter, we provide several pieces of descriptive analysis, based on historical data, to suggest directions for research and policy-relevant issues, drawing from previous work and the fast-growing literature on AI and the labor market.

The discussion below proceeds as follows. First, we examine some indicators of the fluidity of the labor market, reflecting the frequency of workers' transitions across jobs, occupations, and industries. While these are based on historical data, they are suggestive of older workers' potential ability to reallocate from shrinking parts of the economy towards growing ones, thus contemporaneously supporting and adjusting to structural changes.

As a next step, we narrow down our analysis to the likely impact of AI and discuss whether older workers are a priori more or less exposed to its likely positive and/or negative effects. To this end, we employ the measure of AI occupational exposure proposed by Felten et al. (2021) and that of potential complementarity from Pizzinelli et al. (2023) to identify which occupations are more likely to be positively or negatively affected by AI. We also discuss the general features of these occupations, and hence how the reallocation of employment across them could indirectly also increase the availability of jobs with features aligned with older workers' preferences, in turn supporting longer working lives.

Understanding what may happen to *future* generations of older workers, however, requires adopting a more dynamic view of the labor market's adjustment to AI. To this end, we take as case studies the waves of structural transformation unleashed by routine-biased automation in the second half of the 20th century and computerization in the early 21st century, tracking the changes in employment over several decades for different birth cohorts. These historical episodes suggest that the employment structure of workers who are currently young or in their prime, once they reach old age, may be quite different from that of the current cohort of older workers.

We next briefly discuss additional channels and directions for future research. The interaction between AI and aging-related shifts in labor demand and supply opens a broad range of possibilities. In particular, aging societies face heightened demand for jobs in the medical and care services sectors, where AI technologies are being explored to perform key tasks not only in diagnosing and treatment but also in personal companionship. Moreover, improvements in general health thanks to AI technologies may enable a higher share of workers to remain active in the labor market at older ages. Third, as work is not the only source of earnings for households, we consider the implications of AI-driven growth for income from equity holdings, which may play into households' work and retirement decisions, with potentially important consequences for wealth inequality.

Finally, we summarize recent attempts to codify the essential elements of so called 'AI literacy,' and the kind of educational initiatives that can help deliver it to older workers. This concept, of which multiple similar definitions exist, broadly refers to the essential knowledge and understanding of AI and its applications needed for effective and safe use, both in general terms and narrowly within the context of one's own field of work.

Before proceeding, some clarifications on the data and analytical choices we make below are in order. We study historical patterns of labor market transitions and employment using multiple microdata sources produced the US Census Bureau. The Current Population Survey, over 2010-2019, spans the period between the recovery from the Great Recession and the COVID-19 pandemic. This interval of time is both long enough and recent enough to represent the pre-AI labor market trends while avoiding the two large macroeconomic shocks of the past 20 years. More recent waves, from 2023 and 2024, are used to examine general features of occupations regarding workers' health conditions and their ability to telework, grouped by their exposure to AI (US Census Bureau 2010-2019, 2023-2024). The analysis of past waves of structural transformation uses the US Census 1 percent Decennial Sample for each decade from 1970 to 2000 (US Census Bureau 1970, 1980, 1990, 2000) and the American Community Survey for the years 2010, and 2019 (US Census Bureau 2010, 2019).

Throughout the text we use the term 'older workers' to refer to individuals age 55+. For practical purposes, our analysis considers the age range 55-69. While employment above the age of 69 is becoming more and more common, over the period considered most people older than 69 were not in employment, and those who were employed comprise a unique group whose key features differ substantially from the wider population. For comparison, descriptive statistics for older workers are contrasted to the 'prime age' group, comprising the age range 35-54, and younger workers, in the range 21-34.

Our analysis often distinguishes between individuals with a post-secondary degree, referred to as 'college' workers, and those with a high-school degree or below, referred to as 'non-college.' This distinction is important because these two groups tend to be employed in different occupations and industries, and thus also face distinct labor markets in their late careers. For conciseness, we will only focus on male workers. The results presented, including those related to differences across education groups, also hold for females and are available in the Online Appendix. Nevertheless, it should be highlighted that there are many concerns specific to women with regards to late careers and retirement (e.g., Price 2002, Jefferson 2009, Goldin and Katz 2017, Lusardi and Mitchell 2017), whose interaction with technological change and AI is deserving of a separate discussion.[3]

Finally, to keep the discussion self-contained, our analysis focuses narrowly on the impact of AI on labor market opportunities and decisions regarding retirement. There are of course other ways through which AI will shape the lives of older individuals, both during their working years and afterwards, such as by improving healthcare and elderly care technologies. These channels have broader implications which may also interact with older workers' labor market decisions.

Labor market fluidity over the life cycle

The first question we examine is whether, in general terms, older workers are well predisposed to face structural change. Such episodes may entail prolonged periods of disruption in the labor market, requiring moving from shrinking industries and occupations towards those experiencing growing labor demand.

To address this question, we consider several indicators of labor market fluidity, a term proposed by Molloy et al. (2016) to capture the degree to which workers move across jobs, occupations, and industries, possibly experiencing spells of unemployment along the way. While the measures are based on historical data, they are suggestive of workers' potential ability to relocate from shrinking parts of the economy towards growing ones, thus contemporaneously supporting and adjusting to structural changes. Figure 1 reports five transition rates computed at monthly frequency: job finding, separation, job-to-job, industry switching, and occupation switching rates.

Figure 1 here

The job finding rate is the probability that an unemployed worker finds employment within a month, reflecting a worker's ability to respond to a negative shock (of job loss). The evidence shows that older workers have lower job finding rates than their young and prime-age peers; the difference is particularly stark for those with a college degree. While it takes just below three months for a young college-educated worker to find a job on average, it takes approximately two additional months for an older one.[4] This gap is in line with Molloy et al. (2016) and Chan and Stevens (1999), who concluded that job loss has more severe adverse consequences for older workers. This can even lead to early retirement when re-employment opportunities are scarce.

Separation rates represent the probability that an employed worker is unemployed in the following month.[5] This transition could be caused by a layoff, the lapsing of a fixed-term contract, or a voluntary quit—whereby a worker decides to terminate a current job despite no prospects of immediate employment somewhere else. Distinguishing between these reasons is important to understand from a policy perspective the underlying labor market conditions they reflect. Layoffs are most closely linked to negative adverse shocks, and thus unpredictable risks on workers. The ending of a temporary job, while more predictable than a dismissal, can also be considered a source of negative risk, since it entails a period of search for new employment opportunities with uncertain outcomes. Finally, voluntary quits are reflective of workers' propensity to take risks in order to move on to potentially better jobs.

Older workers face lower separation rates than younger ones, particularly in the non-college group. In light of the possible reasons for employment-to-unemployment transitions discussed above, this finding suggests that older workers experience lower exogenous risk to their employment but also take fewer voluntary risks due to their more limited ability to find new jobs, as reflected by their lower job finding rate.

Job-to-job, industry, and occupation switching rates report the probability that a worker changes employer, industry, or occupation (either staying with the current employer or moving to a different one) across two months.[6] These transitions are often associated with increases in wages, especially when they are voluntarily made to pursue better opportunities, and thus they constitute an important driver of workers' income growth over their careers (e.g., Moscarini and Postel-Vinay 2017, Kambourov and Manovskii 2009). These rates also offer useful insights when considering the labor market's adjustment to the sectoral shifts that AI may bring about. In fact, the historical frequency of such transitions provide some indication of workers' ability to relocate across firms whose fortunes may be diverging, away from disappearing sectors and occupations, and into expanding ones. All three switching rates are lower for older workers compared to their young and prime-age counterparts, suggesting that, ex-ante, individuals approaching retirement are less predisposed to career changes.

Overall, Figure 1 shows that older workers' labor market experience is characterized by lower fluidity, with fewer transitions in and out of employment and across jobs, industries, and occupations. This result is in line with earlier studies, in particular Molloy et al. (2016), who also concluded that the lower fluidity of older workers, combined with demographic aging, is the main force underpinning the secular trend of lower fluidity at the national level. While these authors did not explore the reasons behind older workers' lower fluidity, there are several likely drivers, some of which are discussed in more detail later in this chapter. Older workers are more often already at the peak of their careers, where they have reached close to their potential earnings in their chosen career path. They therefore see less need to voluntarily make career changes and, due to their longer tenure, are less vulnerable to dismissals and contract terminations (either foreseen or unforeseen). Meanwhile, their longer tenure in a given career may mean that their skills are less transferable, thus reducing prospects for changes in jobs or for finding new employment with desirable salaries when jobless.

AI and Jobs: Exposure and Complementarity to AI

While the previous section considered the general labor market dynamics of older workers, it did not explore whether older workers would be affected by AI-driven structural change in the first place. This section therefore offers a tentative appraisal of whether AI is likely to produce significant transformation in the labor market of older workers.

Of course, given the early stages of adoption and the continuous development of new AI technologies, predictions remain uncertain. Nevertheless, it is useful to spot demographic groups that, on average, are better positioned to fill roles in expanding occupations or that may be worse hit by declining labor demand in other occupations.

We begin by identifying the occupations where AI can be expected to perform some of the essential tasks. Moreover, among these jobs, a crucial distinction must be made between those occupations where the extensive use of AI will plausibly substitute for human labor in the performance of these tasks, versus those where AI will be supervised by humans, thus serving as complementary technology. The workers employed in the former would face higher risks of an adverse impact from AI in the form of declining demand for their labor, fewer positions, lower wages, or even outright displacement. Meanwhile, conditional on possessing the skills needed to use AI technologies, those in the latter group of occupations are likely to enjoy the benefits of higher productivity, growing labor demand, and more abundant employment opportunities.

Several studies propose classifications that, based on the key tasks performed and skills required, measure occupations' 'exposure' to AI (Eloundou et al. 2024; Felten et al. 2021, 2023; Gmyrek et al. 2023; Pizzinelli et al., 2023; Webb 2020). Some authors, such as Eloundou et al. (2024) and Felten et al (2021, 2023), considered definitions of exposure that measure the scope for AI use within an occupation. For instance, Felten et al (2021, 2023) defined exposure as the overlap between 10 AI applications (e.g., image recognition and generation, text comprehension, writing) and 52 human skills (e.g., oral comprehension and expression, hand-eye steadiness, inductive reasoning), which are then weighted by their importance for an occupation as measured by O*NET (O*NET 2023), a detailed public database of information on standardized job titles. Nevertheless, these definitions do not identify the effect that AI use would have on workers in those jobs. Other authors, such as Gmyrek et al. (2023) and Pizzinelli et al. (2023), go a step further to provide an assessment of the potential implications for workers, making a distinction between substitution (also called automation) and complementarity (or augmentation).

Here, we follow Pizzinelli et al. (2023) to focus on older workers, measuring AI's labor complementarity at the occupation level. Expanding on the AI occupational exposure (AIOE) measure of Felten et al. (2021), they posit that, while exposure reflects the potential for AI use, the decision to adopt AI will ultimately depend on a broader range of practical constraints, social preferences, and ethical concerns. Drawing from O*NET's 'job contexts' section, they consider six themes for the use of AI: (1) in-person and public interactions, (2) personal responsibility for errors, (3) criticality of jobs and health and safety concerns, (4) the physical settings of work, (5) the frequency of independent decision-making and unstructured tasks, and (6) the years of education and training required to fulfill the position. The rationale for this approach is that aspects of a job connected to these themes will involve societal preferences and concerns that may limit, at least in the short term, the application of AI to perform major tasks without human supervision. These occupations therefore entail different degrees of complementarity between AI and labor. Workers employed in occupations with high complementarity would be more likely to experience a productivity boost from AI, while low complementarity would be associated with a higher risk of a decline in labor demand.

Figure 2 shows how standard job titles score in terms of exposure and complementarity, with some selected occupations to provide intuition for the classification. For example, let us consider professions in the legal field. Legal assistants, lawyers, and judges have very similar levels of AI exposure on the x-axis, reflecting the similar skills and tasks involved in these jobs: retrieval of information, comprehension of complex texts, and technical writing. Yet, complementarity differs markedly across the three jobs. Legal assistants have the lowest level of complementarity, as their roles involve less independence, more routine tasks, lower personal responsibility, and fewer high-stakes decisions. By contrast, lawyers undertake more in-person interactions with clients and counterparts, and they bear greater personal responsibility for the outcomes of actions whose implications may be highly consequential for other individuals. It is thus plausible to imagine that, in the near term, firms and clients are less likely to accept that key tasks of a lawyer would be executed in an unsupervised manner by AI, compared to delegating some of the more standard activities performed by legal assistants. Given the critical social role played by judges, safety and ethics concerns would further limit substitution by AI in their key functions.

Figure 2 here

High-Exposure Jobs and Older Workers

Following Pizzinelli et al. (2023) and Cazzaniga et al. (2024a, b), we group occupations into three categories: high exposure and high complementarity (HEHC), high exposure and low complementarity (HELC), and low exposure (LE). The first and second groups comprise those occupations expected to be most affected by AI positively and negatively, respectively, while the last one includes those where the implications of AI will likely be mild. The threshold values to label occupations as 'high' in terms of these two dimensions are based on the median values of the two indicators.

This grouping simplifies the analysis when dissecting the labor market along multiple dimensions, such as age and education, highlighting the most substantial differences across demographic groups. It is therefore a useful approach to take an initial snapshot of the labor market and draw early conclusions. However, it inevitably implies a loss of detail, which would be necessary for drawing more focused conclusions at later stages. For instance, there is large variation in exposure and complementarity within each of these categories, and some occupations lie very close to the threshold values. Hence, the intended use of the grouping is to provide a lens to understand the general features of the labor market rather than make a strong deterministic judgement on the impact of AI on a given occupation.

A snapshot of employment composition. Equipped with this categorization of occupations, we now paint a broad picture of workers' exposure to AI across the age distribution, considering the potential for both disruptions and positive effects.

Figure 3 plots the share of employment in HEHC, HELC, and LE occupations for non-college and college workers, separately at different ages. For both groups, those age 55+ are employed in HEHC in larger shares than prime-age and young workers with the same educational attainment. By contrast, employment in HELC and LE occupations falls as workers age and move into HEHC jobs. As Cazzaniga et al. (2024b) note, given that HEHC occupations also feature higher wages than HELC and LE ones, career advancement into these jobs is also associated with income growth. This progression, particularly over ages 20's and 30's, is especially pronounced for college graduates. Although non-college workers feature a high share of LE employment at all ages and a more modest rise of HEHC jobs through their careers, the differences between young and older workers in this group are also evident.

Figure 3 here

Based on current employment composition, the current generation of older workers appears relatively better positioned to reap the productivity-enhancing effects of complementarity with AI and more sheltered from the potential adverse implication of AI-driven labor substitution. Moreover, despite the finding from the previous section that older workers are less prone to adjust their careers versus their younger peers, the fact that the types of jobs with more potential to grow are those in which they are already employed in relatively higher shares is encouraging, with regard to their predisposition to move into these roles in greater numbers.

An important caveat to this conclusion, however, is that Figure 3 focuses on age differences *conditional* on being in a given education group, and there is a large gap in the share of HEHC employment between workers with a college degree and those with at most a high school diploma, especially for the older age group. Hence, education is likely to be an important factor, or at least a predictor, of workers' vulnerability and potential to benefit from AI. When considering cross-age heterogeneity, recent generations (currently in their early career or prime working age) have higher shares of college degrees than older generations: in 2023, 47 percent of men age range 25-34 had completed an associate or bachelor's degree, compared to 44 percent age 55-69.[7] The gap is even larger among women: the college attainment rate in 2023 was 57 percent for those age 25-34, compared to 47 percent of those age 55-69. Hence, since college-educated workers have higher employment shares in HEHC jobs, the unconditional age-based differences in AI exposure are somewhat mitigated by the higher university attainment of younger generations.[8]

An additional qualification to our conclusion concerns the skill requirements to work with AI. An occupation's complementarity with AI would not necessarily translate into higher productivity and wages for all those currently employed in it, since having the necessary knowledge and skills is a prerequisite to not only benefit from these developments, but also to be shielded from potential disruptions. It is yet unknown exactly what skills will be needed in different jobs to work with AI, but they are likely to vary substantially in both range and depth. OECD (2023) made an important distinction between jobs where AI development skills will be essential, versus those, possibly the majority, where workers will need a certain degree of AI literacy. The former entails more fundamental knowledge and the ability to develop or at least interact with AI models at a more technical level, while the latter only requires understanding the general principles of AI and the ability to properly interpret its output in a job-specific context. The latter skills would be simpler to acquire through targeted training, especially for older workers.

The age-friendliness of HEHC jobs. Having discussed older workers' risks and opportunities from AI-driven labor market changes in the near term, we next consider the broader implications for labor force participation and retirement.

Cazzaniga et al (2024b) noted that, in the UK and Brazil, among the three broad occupation groups, HEHC jobs exhibited the highest average wages, followed by HELC, and with LE last.

This is only partially explained by demographic characteristics (gender, education, and age) of the workers who fill these positions. The first panel of Figure 4 shows that the earnings premium of HEHC jobs exists in the US as well.

Figure 4 here

The evidence linking high earnings and the timing of retirement is somewhat mixed. On the one hand, greater accumulated savings may allow workers to secure the finances needed to fund their retired life at a younger age, especially in a context where defined contribution (DC) pension schemes are the norm. On the other hand, workers earning a high income from their jobs have a greater incentive to continue working to accumulate additional savings for retirement. Also, higher incomes are associated with greater economic stability, job satisfaction, and better health outcomes (Congdon et al. 2021), factors that increase older workers' wellbeing and would ultimately empower them to make less constrained decisions regarding when to retire.[9]

Other aspects of jobs also play an important role in determining people's satisfaction with their work and hence their labor market attachment. Of course, preferences over job characteristics may vary across age groups, as physical capacities, ambitions, life priorities, and other personal circumstances change (Acemoglu et al. 2022b). Several studies, including Maestas et al. (2018) and Ameriks et al. (2020) found that older workers especially value autonomy and flexibility in setting their schedules, lower intensity of physical effort, lower mental stress levels, shorter commuting times, and the ability to telework. Evidence from the US (Hudomiet et al. 2019) as well as other industrialized economies (Angrisani et al. 2020; Cantareto-Prieto et al. 2018; Gielen, 2009; Sousa-Ribeiro et al. 2024) shows that such old age-friendly characteristics are associated with longer careers and later retirement.

The other panels in Figure 4 show that several features aligned with older workers' preferences and proxies for high job quality are, in fact, more prevalent among HEHC occupations. Working from home is more common in these occupations, especially compared to LE ones, coincident with more flexible working arrangements. Workers in such jobs also report lower levels of health-related difficulties. This could be a consequence of the fact that many LE jobs involve predominantly manual tasks, which over time could be conducive to work-related injuries and health problems. Some evidence in support of this hypothesis comes from the fact that a lower share of people in HEHC occupations is employed in physically intense jobs, as seen in the bottom left panel. Yet, despite an equally low share of employment in physically intense jobs, workers in HELC occupations report a higher rate of physical difficulties compared to those in HEHC jobs. Hence, the higher income earned by workers in HEHC jobs may allow them to maintain better health conditions throughout their lives.

Some features of HEHC occupations, however, may not be conducive to longer working lives. For instance, as shown in the last panel in Figure 4, the share of workers in high-stress roles is substantially higher than in HELC and LE occupations because HEHC jobs involve critical decision making and more responsibility.

Long-term transition and future generations of older workers

Thus far, the discussion has focused on near-term AI-driven structural transformation, implicitly asking what the implications for those who are *currently* old will likely be. We turn next to a longer-run perspective. This is important as the integration of innovations into productive activities can take decades, requiring large financial investments, fine tuning, the invention of supporting tools, and the difficult restructuring of old processes (Brynjolfsson et al. 2017, 2021).

Accordingly, the implications of AI adoption for *future* generations of older workers may be quite different.

The different baseline propensities for changing occupations and industries of employment by age may become more pronounced in periods of structural transformation. Adjustment and transition to growing industries may be difficult not just for older workers, but also for prime-age individuals who have already developed sector-specific human capital and may not be able to invest in training to acquire new skills. In contrast, the young may be able to switch more easily across entry-level positions in different industries without large or persistent falls in income. Moreover, they have greater incentives to adjust: with longer careers still ahead of them, choosing the right sectors and occupations will have greater consequences for their lifetime earnings. Indeed, the high switching rates shown in Figure 2 indicate that frequent job, occupation, and industry changes are already an inherent component of young workers' labor market experience as they shape their career paths. Hence, the shifts induced by AI would require a reconsideration of their envisioned professional trajectories, rather than a reaction to an unexpected external shock.

Finally, new generations yet to reach working age will likely benefit from revamped educational curricula that equip them with the newly demanded skills. They will also have the ability to choose their fields of study with better information on which sectors are growing the fastest. They will arguably be in the best place to seek employment in the most in-demand occupations and industries upon entering the labor force, with repercussions for their earnings at the time of retirement decades later.

Routine-biased automation as a case study. Past episodes of technological innovations demonstrated that the adjustment to the shifting labor market can be asymmetric across age groups. For instance, the wave of automation that began in the 1970's had particularly adverse consequences for middle-aged workers. This process initially entailed mostly the substitution of repetitive manual functions by machines, primarily concentrated in industrial production within the so called ‘blue-collar’ sector. In more recent decades, however, automation spread more broadly across the economy through computer technologies, which led to the disappearance of cognitive-based routine occupations, in particular clerical and secretarial jobs in the so called ‘white-collar’ sector.

Several studies found evidence of heterogeneity across age groups in the employment displacement induced by these two waves of automation. Autor and Dorn (2009) studied the large reallocation of employment from middle-skill routine-intensive occupations towards both low-pay manual jobs and high-pay cognitive ones. This phenomenon, often referred to as ‘job polarization’ (Acemoglu and Autor 2011), was largely driven by automation technologies replacing workers in routine-intensive occupations, particularly in the manufacturing sector (Autor et al. 2003). Over the period 1980-2005, as the employment share of routine jobs fell, the average age in these occupations rose faster than in the rest of the economy. This led young workers to change jobs in greater numbers, compared to both prime-age and older workers. Moreover, among those who did move out of routine jobs, workers below age 30 were significantly more likely to transition into higher-paying cognitive jobs, while prime-age and older workers more often moved into lower-paying manual jobs.

Hudomiet and Willis (2022) found similar age-based differences with regards to computer-driven automation from the mid-1980s to the first two decades of the 21st century. Within occupations that underwent computerization earlier on, older cohorts of workers, who faced technological change in their careers, acquired new skills more slowly, experienced lower wage growth, and faced a temporary increase in the rate of transition to labor force inactivity.

Further descriptive evidence of this heterogeneity across cohorts appears in Figure 5, showing the uneven decline in manufacturing employment between 1980 and 2000 (left panel) and in routine-cognitive occupations between 2000 and 2019 (right panel) among male workers.[10]

Workers born between 1935 and 1944 were in their late 40’s and early 50’s in 1980. By 2000, the share of manufacturing within this cohort’s total employment had fallen by more than 7 percentage points. Over the same period, the share of employment in industries where average wages were higher than manufacturing also fell, by approximately 2 percentage points. Meanwhile, the employment share in lower-wage industries grew by about 9 percentage points. Hence, in 2000, the 1935-1944 cohort reached the late stages of its career having suffered a particularly severe and persistent economic shock from the disappearance of manufacturing jobs, which resulted in a shift towards lower-paid employment over the course of two decades.

Figure 5 here

The adjustment process looked markedly different for younger cohorts. For the 1945-1955 cohort, the shift away from manufacturing was smaller in magnitude and more symmetric. The 3-percentage point decline in manufacturing employment share was mirrored by a rise in lower-wage industries of approximately 2 percentage points, and a 1-percentage point rise in the share of higher-wage industries. The smaller magnitude of the reallocation is likely explained by the greater ability of these younger workers, in their ‘early’ prime in 1980, to adapt to the new automation machinery within the manufacturing sector, thus becoming more complementary to the new technologies. Those who did move away from the sector may have been better able to pick up new skills or even to move geographically in search for other well-remunerated jobs. Overall, workers in this cohort reached retirement in the 2010s having suffered a milder adverse shock than the older generation.

Finally, for the youngest group of workers, born over 1955-1964, the employment adjustment almost entirely entailed a large reallocation away from low-earning to high-earning sectors. Many of these workers had yet to finish their schooling in 1980, while the older ones were in the very early stages of their careers. Those who were already employed in manufacturing had the ability and strong incentives to transition out of the sector early. Meanwhile, those not employed in manufacturing or still in school had a chance to redirect their trajectories towards other growing and better paid sectors. Hence, this youngest cohort reached retirement in the late 2010s and early 2020s, having suffered minor disruptions from the disappearance of manufacturing jobs and having had the chance to pursue opportunities in other growing sectors.

The right panel of Figure 5 shows very similar patterns with respect to the decline of routine-cognitive occupations in the first two decades of the 21st century. Between 2000 and 2019, the aggregate share of employment in routine-cognitive occupations fell by 4 percentage points, declining by just slightly more than 1 percentage point for males and more than 7 percentage points among females. The 1955-1964 cohort, in their prime years in 2000, barely experienced any fall in this share over the following two decades. The 1965-1974 cohort experienced a decline in the routine share of about 2 percentage points, joint with an additional 1-percentage point fall in the share of occupations with a lower average wage, and a 3-percentage point rise in employment in higher-earning occupations. Meanwhile, the 1975-1984 cohort, the youngest one to be of working age by 2000, saw a very large shift away from routine-cognitive occupations as well as jobs with lower wages and a 25-percentage point rise in the share of higher-earning occupations. While this large shift is partly aligned with life-cycle trajectories and career progression, similar to those shown in Figure 4, it also reflects the greater educational attainment of younger generations, as suggested by higher college attendance rates, which resulted in greater employment in high-earning jobs.

It is unclear whether similar cohort-based differences in the capacity to navigate technological transformation will hold for AI. Some of the premises still remain the same, since it is still the case that older workers are generally less flexible but also very close to finishing their careers. As shown in Figure 1, prime-age workers may be slightly more resilient, but those in HELC occupations will face disruption just when their earnings tend to peak and their professional trajectories are settled. As before, younger workers will adjust and acquire new skills through both formal education and online courses. Nevertheless, AI differs from automation technologies in ways that could produce different adjustment patterns. For instance, its wider range of applicability implies that AI adoption will span multiple industries. In contrast, early automation, with its heavy concentration in manufacturing, was a sector-specific and in many cases highly geographically concentrated shock, so affected workers had limited prospects in other industries. By contrast, later automation, driven by digital technologies, affected cognitive-intensive routine occupations that often cut across industries. As such, it more closely resembles the type of disruption that AI might entail. Nevertheless, the past digitalization wave may be a mitigating factor with respect to the potential disruptions of AI. As a direct consequence of the computerization of many jobs, most workers today, even of older ages, are already very familiar with digital technologies and possess basic IT skills. Therefore, they could easily become proficient in using AI-based technologies, thus facilitating their employment in HEHC occupations.

Still, however, the historical experience of routine-based automation shows that the ultimate impact of technological transformation on workers' individual outcomes depends crucially on the career stage when it is experienced. With this in mind, policymakers and employers may wish to consider initiatives that encourage workers of all ages to 're-skill,' tailored to their abilities to move to new sectors and their remaining work lives.

Other channels and related issues

In this section we provide a brief discussion of other channels through which AI adoption and aging trends may interact, with implications for older workers' labor market decisions.

Growing demand for aging-related jobs. Demographic aging has fueled a growing demand for health and long-term care services. This has resulted in a shortage of personnel in related professions (e.g., Paulin 2022, Zucker 2025), which has added to long-standing cost pressures in these sectors, particularly in the US. Out-of-pocket spending on health and long-term care (both at home and in retirement facilities) is particularly high late in life (Banerjee 2025), posing critical financial risks to older households. It is therefore no surprise that efforts to develop AI applications in aging-related health and care services have been significant in recent years (Rubeis 2020, Loveys et al. 2022), via both monitoring and diagnosis technologies and in the form of service robots for the performance of care tasks and general companionship.

These AI applications nevertheless remain at an early stage and are accompanied by a vibrant discussion on how to address the still somewhat limited patience acceptance (Li et al. 2024), due to a preference for human interaction, and foster ethically responsible use (Lukkien et al. 2021, Ho 2020, Rubeis 2020) with respect to critical decisions and access to sensitive patient data. Based on the conceptual framework we have used in this chapter, the importance of in-person interactions for some care services and ethical concerns point to a greater likelihood of AI being adopted as a complementary technology. Hence, it is plausible that AI would assuage cost pressures from labor shortages in health and long-term care but would not altogether lower the demand for labor in these fields. Most likely, while wages in related occupations may not rise as much as in a scenario of strong labor shortages, the use of AI-related technologies may require doctors, nurses, and other professionals to acquire new skills (Groenveld et al. 2025, Wong et al. 2024), which may lead to higher wages in line with their greater human capital.

AI-driven improvements in health outcomes. Another matter related to the interaction between AI adoption and labor markets regards how AI technologies can lead to improvements in health. which would in turn enable older workers to remain active in the labor market for longer. Health shocks are an important factor in early retirement (Sislov and Chung 2025). Improvements in health outcomes delivered by better prevention or treatment via AI-based technologies could therefore have a direct impact on older workers' ability to remain active later in life. Moreover, indirectly, better health or cheaper care services provision could help workers avoid having to move out of employment in order to tend to the care of family members with disabilities or health-related limitations.

Equity income. Even though paid work is the main source of income for most people, households may incur economic benefits from AI not just through their own labor but also through higher returns on their equity holdings. If AI boosts firms' productivity, the expectation of higher future profits would raise the value of their stocks and dividend payouts, increasing the wealth and income of those who own them (Rockall et al. 2025). This channel would be particularly relevant for older workers, who on average own larger amounts of equity assets.

The increase in non-labor income may in turn affect older workers' labor supply and retirement decisions, although the relationship is a priori ambiguous. On the one hand, greater wealth and higher expected assets returns to support households' income during retirement reduce the need to work additional years to contribute to pension funds, thus allowing for an earlier retirement. On the other hand, the relatively high wages typically earned in the late stage of their careers may induce older workers to postpone retirement for a few years to save a large portion of their earnings in fast-growing equities to further increase their future income from the accumulated assets. Not only is the relevance of these channels quite uncertain, but they may also be highly heterogeneous across the population, as a substantial share of older households own little to no equities (Fagereng et al. 2017).

Heterogeneity among older workers. Finally, for conciseness, this chapter discussed older workers as a single group, only making distinctions between men and women and across education levels. Other dimensions of heterogeneity, not examined here, may be salient. For instance, geographic regions are often specialized in specific industries, which may lead to large positive or negative shocks as those sectors either benefit from or are disrupted by AI. Some early signs of this dynamic are found by Bonfiglioli et al. (2025) and Pizzinelli et al. (2023).[11] The former showed that employment, particularly of lower-education workers, has been adversely affected in metropolitan areas with greater AI adoption. The latter found that, over 2022 and 2023, the share of online job vacancies for HELC jobs declined more in cities with greater concentration of industries that had an earlier adoption of AI. This channel would interact with aging if, for instance, older workers were concentrated in areas where there is lower AI growth. A priori, this link is still ambiguous. White collar jobs, both of HEHC and HELC types, are predominantly located in larger cities, where the concentration of older workers is lower. Differences across race are also deserving of additional study, if anything because race is correlated with other factors such as educational attainment, income, and geographic distribution. Moreover, there is evidence of gaps in average digital proficiency and access across ethnic groups (Hecker and Briggs 2021, Darko et al. 2023), which could lead to disparities in the ability to harness AI in growing occupations. This may be particularly problematic for older workers since, as noted above, they have lower propensity to acquire new skills over the remaining years of their careers.

Fostering AI literacy

Before concluding, it is worth discussing briefly what abilities and knowledge may be needed to successfully navigate the AI-driven wave of structural transformation and what older workers can do to acquire them.

As noted above, AI-relevant skills do not necessarily entail fundamental knowledge and ability to work directly with AI models, but they can also include more general AI literacy skills. Fundamental AI skills will only be needed by those employed in fields related to the development and active application of AI or where it will substantially change the set of core competencies, such as many IT, engineering, and data science positions.

On the other hand, AI literacy refers to the ability to be a productive and conscious user of AI technologies, in broad terms and in the narrower scope in which it is applied to one's field of work. This concept centers around AI-aided decision making, placing particular emphasis on data inputting and interpretation of AI's outputs, including error detection. Reflecting the broad range of potential AI applications, it is on purpose generic, but there have been efforts to define the core components of AI literacy, whose exact definition can then be tailored to individual fields. Among academic studies, recent attempts to a definition include Long and Magerko (2020), Casal-Otero et al. (2023), Chee et al. (2024), and Ng et al. (2021). For example, the latter study, based on a broader review of the literature, identifies four pillars of AI literacy: understanding, use, evaluation of output, and ethical issues. Recently, the OECD and the European Commission have also proposed a similar working definition, which identifies four core competencies, whose details can evolve over time: engaging with AI, creating with AI, managing AI, and designing AI. Each of these domains in turn requires appropriate foundations with respect to knowledge, skills, attitudes, and ethics (OECD 2025). Moreover, other studies have explored AI literacy competencies for individual professions, including engineering (Cantú-Ortiz et al. 2020), medicine (Wartman and Combs 2019), and nursing (Groenveld et al. 2025, Swan 2021).

AI literacy requires less extensive training than fundamental AI skills. While it should become a component of the standard educational curriculum for future generations, it can reasonably be also gained with targeted courses, micro-learning certificates (such as those often provided by online education platforms), and on-the-job training, especially when narrowly focused on applications in a specific profession. This type of training is possibly simpler to deliver and can be integrated in the kind of regular professional development programs that most companies already run (e.g., on cyber risks, ethics, financial literacy, retirement planning).

Programs have varied widely in nature across firms that have taken the initiative to create structured courses for their employees, and no standardized curriculum exists. However, the EU offers one useful source to get a sense of current firm-level initiatives. Article IV of EU AI Act establishes the requirement for companies using AI to ensure AI literacy of their staff. To aid this effort, the EU provides links to general courses as well as a ‘living repository of AI literacy practices’ from large EU firms that have volunteered to share their educational initiatives (European Commission 2025). Most of the listed initiatives follow the broad features described above, combining a general understanding of the technology with more specific discussions of its application in the firms’ lines of business. Notably, as of June 2025, only two companies made a explicit reference to senior professionals and older generations in their initiatives, citing them as a category particularly averse or challenged by changing work practices and technologies, and thus a key target for training programs.

Conclusion and Policy Implications

This chapter examined the potential implications of AI-driven structural change for older workers. Overall, we paint a mixed picture, not only because the ways in which AI will be applied in many contexts remain uncertain, but also because it will interact with several aspects of older workers' decisions in confounding ways. At present, a higher share of older workers, especially those with a college degree, is employed in high-complementarity occupations likely to benefit from AI more than young and prime-age workers, and fewer are employed in low-complementarity occupations at greatest risk of disruption. The high-complementarity occupations are also associated with higher earnings and offer features aligned with older workers' preferences, such as lower levels of physical intensity. Thus, an expansion of these jobs may also encourage longer careers and higher labor force participation among the over-55.

Nevertheless, older workers are generally less mobile across employers, occupations, and industries than are the young and prime-age groups. They also face lower re-employment chances when unemployed. Hence, despite their lower exposure to risks from declining labor demand or job destruction, they may become more vulnerable if these shocks materialize.

Structural transformation will take place over the course of several years, as new AI technologies help replace older production processes. Hence, the implications for future cohorts of older workers may differ substantially from those for the current generation. Our case studies of the impact of routine-biased automation suggest that workers in their prime years who are employed in highly disrupted industries and occupations could be most vulnerable to long-lasting adverse shocks. This group might not be much more resilient than current older workers in its ability to re-adjust to a shifting labor market. The scarring effect of the disruption may persist through a more significant stretch of their working lives, thus implying a much larger fall in total lifetime earnings by the time they reach old age. Meanwhile, young workers may be able to more swiftly adjust to growing sectors and thus benefit from the opportunities brought by AI throughout their full careers. They could be likely to reach retirement age with a lifetime of higher earnings and greater accumulated savings.

Other indirect channels linking aging and AI may also play a role. For instance, the growing need for workers in the health and long-term care sectors is spurring research for AI applications in these sectors which are very likely to be labor-complementary. Improvements in health driven by AI technologies may also in turn enable more older workers to remain employed later in their careers. Finally, while paid labor remains the primary form of income for most households, increased returns from equities, as firms adopting AI see rising productivity and profits, could also be an important source of earnings for many—though not all—older households. Particularly in a DC pension system, this channel might play a non-trivial role in decisions regarding the timing of retirement.

Faced with this mixed picture, designing detailed policy responses is challenging, yet some crucial opportunities to prepare for change emerge. First, providing opportunities for training and 'lifelong learning' would allow workers to become AI literate and repeatedly update their skills, so as to acquire new human capital when needed (Aisa et al. 2023, Casas and Román 2023). While firms should already have an incentive to maintain their workers' skills relevant and enhance their productivity, some may not have the foresight to do so. In those instances, support to employers (e.g., through tax deductions or grants) to provide on-the-job training, with a focus on basic AI literacy as well as growing labor force needs, and targeted to at-risk groups such as older workers, could be helpful. Of course, active training and re-skilling programs would also be crucial for the unemployed to find new career paths.

The labor market disruptions that AI could bring about may also call for an overall strengthening of social safety nets, since behind many of the averages and trends discussed in this chapter there was wide heterogeneity. Technological change may ultimately lead to greater productivity and prosperity for the economy as a whole, yet short-term disruptions may be severe and have long-lasting adverse consequences for individual workers unable to navigate these structural shifts alone. Social safety nets could reduce the number of individuals who fall through the cracks during this adjustment process, contributing to a smoother transition.

For older workers, a strong safety net would ensure that economic shocks in the late stages of their careers can be dampened. This could happen, for example, if job losses a few years before retirement were to translate into very large losses in future social security or DC pension benefits. Nevertheless, the design of such benefits must continue to provide people with incentives to search for new employment, even if at lower wages, instead of pushing them to leave the labor force prematurely.

Finally, policymakers can begin to think of aging and technological change not as two separate challenges to be tackled individually, but as two aspects of a common societal shift. Many technological innovations underpinned the improvements in health and wellbeing that led to higher life expectancy over the past decades. AI is a further step in this direction, not just because it will contribute directly to improvements in healthcare and elderly care (Harris et al. 2025) but also because it opens doors to jobs and career trajectories that may ultimately support longer and better lives. Of course, further increases in life expectancy could be a positive development, yet they would also exacerbate the challenges that aging societies already face. Furthermore, as noted by Acemoglu and Restrepo (2022), aging can be a driving force for continued AI innovation by increasing the demand for automation, as a smaller labor force can boost the returns to labor-substituting technologies.

Ultimately, AI can be a tool for aging economies to progress towards what Scott (2021a,b, 2023) terms 'longevity societies;' that is, a structure in which aging is seen as an active and gradual experience to be managed creatively, with greater participation in the broader community and economy.

Acknowledgments and Disclaimer

The authors would like to thank Olivia S. Mitchell, John Scott, and participants at the Pension Research Council 2025 Symposium for helpful comments. Any errors are their own. The views expressed exclusively represent those of the authors and should not be interpreted as reflecting the official views of the International Monetary Fund, its Management, or its Executive Board.

Notes

[1] A non-exhaustive list of studies of the impact of AI on productivity of specific occupations includes Brynjolfsson et al. (2023), Dell'Acqua et al. (2023), Doshi and Hauser (2024), Kanazawa et al. (2022), Korinek (2023), Noy and Zhang (2023), Peng et al. (2023), and Schoenegger et al. (2024).

[2] Data from the Organisation of Economic Cooperation and Development's demographic database. The old-age dependency ratio is defined as the ratio of the population aged 65 and above to the population aged 15 to 64.

[3] See Cazzaniga et al. (2025) for an overview of the potential impact of AI on women's employment, and Albanesi et al. (2025) for an analysis focused specifically on women in Europe.

[4] This approximation is derived assuming that finding a job can be considered a discrete Poisson process, such that the expected number of months it takes to find a job is computed as 1 over the job finding rate. For young college workers, 1/0.27 = 3.7, while for older college workers 1/0.18=5.6.

[5] The separation rate can be computed either using only employment-to-unemployment flows across two months or considering transitions from employment to all non-employment states, including inactivity. Here we choose to focus on the former as it excludes several types of employment exits that are very frequent among older workers but do not reflect the inherent fluidity of the labor market, such as health-related inactivity and retirement. Employment-to-unemployment flows, on the other hand, reflect layoffs, the lapsing of fixed-term contracts, and voluntary quits.

[6] Fujita et al. (2024) note that changes in the Current Population Survey's questionnaire have led to an under-measurement of job-to-job transitions since 2008, and propose a method to adjust aggregate statistics for comparability with previous years. We do not carry out this adjustment in Figure 1. Nevertheless, to the extent that the statistical issue equally affects all years in the survey and demographic groups, it does not excessively compromise comparison across age and education categories.

[7] The reported share is for the population, unconditional on gender. However, the gap is larger among women, with a share of college-educated 25–34-year-olds of 57 percent compared 47 percent for the 55-69 age group, while for males the respective shares are 47 and 44 percent.

[8] In the 1975-1984 cohort, 55 percent of male workers had a college degree by age 25-29, compared to 52 percent in the 1955-1964 cohort. The differences are markedly larger for women, with 69 percent of those age 25-29 having attended college for the 1975-1984 cohort versus 60 for those born 20 years earlier. Consequently, the asymmetric employment shift away from routine-cognitive occupations over 2000-2019 is even starker for women, as shown in Online Appendix Figure A4.

[9] See Barrela et al. (2025) for a recent discussion of these issues, comparing the cases of Spain and the UK. In particular, they find that in Spain, a country centered around Defined Benefit (DB) pension schemes, there is positive relationship between average earnings and average retirement age across broad occupation groups. This relationship is not present in the UK, where the average retirement age is higher in occupation groups that have lower average earnings and also tend to have higher shares of workers on Defined Contribution (DC) pension schemes.

[10] The definition of routine-cognitive occupations is taken from Cortes et al. (2020), using the US Census 2010 classification. The main occupations in this category in 2000 were concentrated in office activities (e.g., secretaries and administrative assistants, other office clerks, bookkeeping and accounting clerks, first-line supervisors of office and administrative staff) and in sales and customer service positions (e.g., retail salespersons, customer service representatives, first-line supervisors of sales workers, cashiers, receptionists and information clerks).

[11] This result is available in an updated version of Pizzinelli et al. (2023), which is available on the authors' websites.

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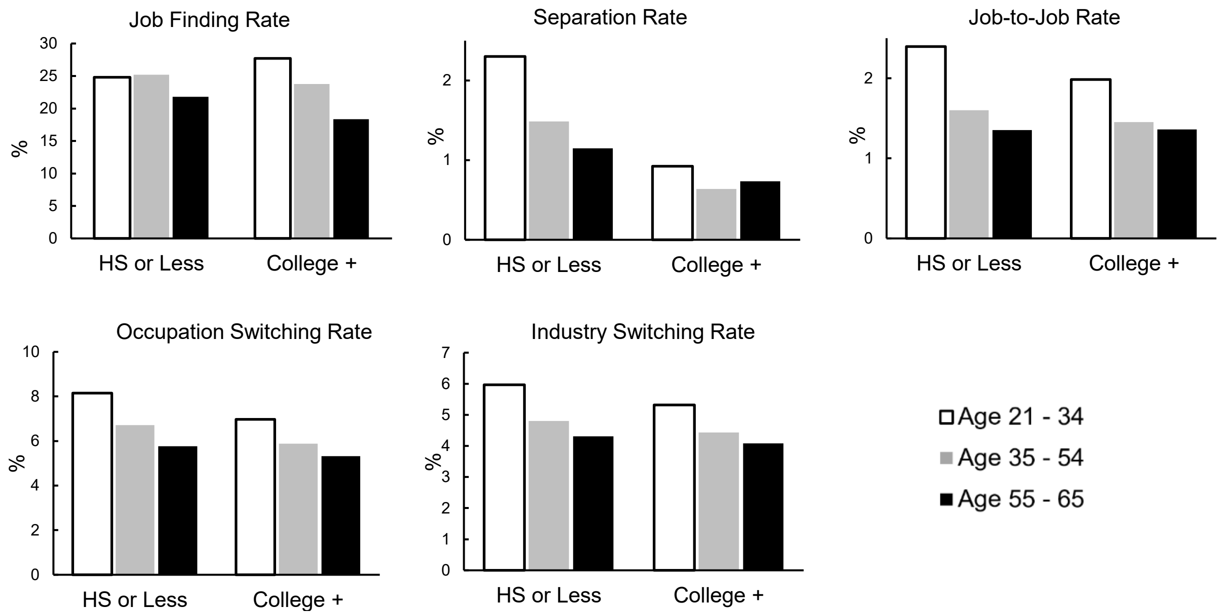


Figure 1. Indicators of labor market fluidity by age and education, men only, 2010-2019 averages.

Note: The top left panel reports the job finding rate for unemployed workers, defined as the probability of being employed in the following month. The top central panel reports the separation rate among employed workers, defined as the probability of being unemployed in the following month. The top right panel reports the job-to-job rate among employed workers, defined as the probability of working for a different employer in the following month. The bottom panels show the industry and occupation switching rates among employed workers, defined as the probability of reporting two different industries or occupations of employment across subsequent months. Industries are defined based on the 4-digit NAICS and occupations are defined based on the 4-digit Census classification. The sample include male workers over 2010-2019.

Source: Authors' calculations using data from the Current Population Survey 2010-2019 (US Census Bureau 2010-2019).

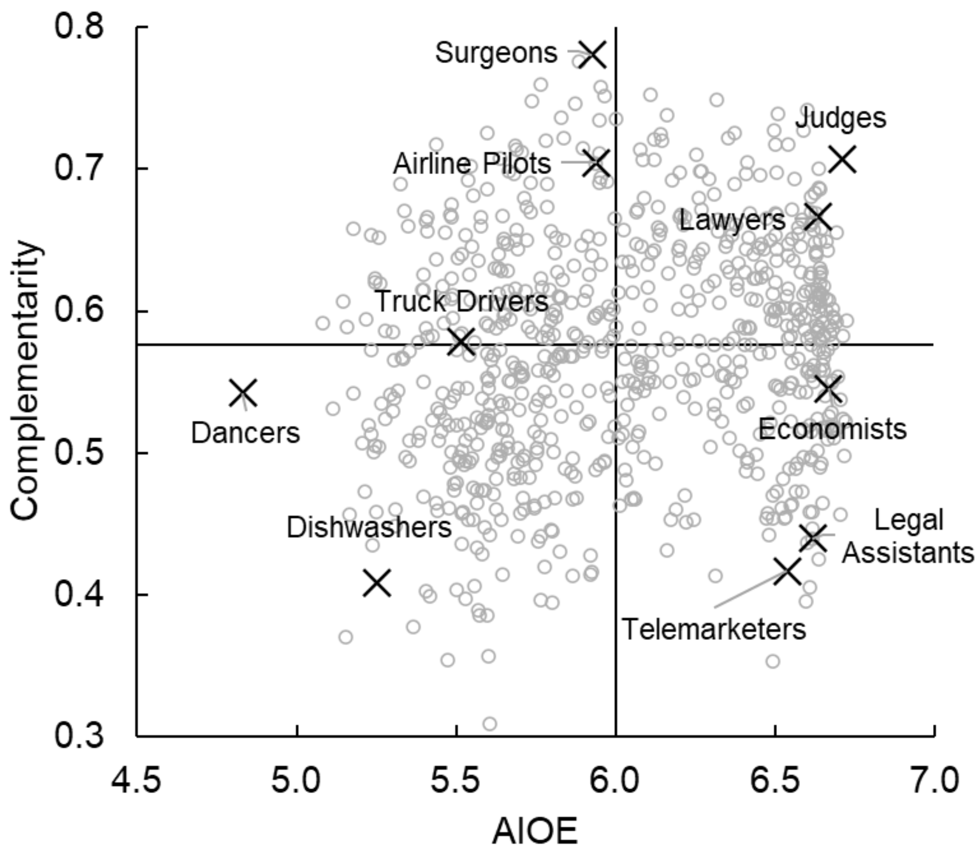


Figure 2. AI Occupational Exposure (AIOE) and Complementarity for the US SOC 2010 classification.

Note: The figure plots the raw value of the AI Occupational Exposure (AIOE) index from Felten et al. (2021) and the AI complementarity index from Pizzinelli et al. (2023) for 4-digit US SOC 2010 occupations.

Source: Authors' calculations using data from Felten et al. (2021) and Pizzinelli et al. (2023).

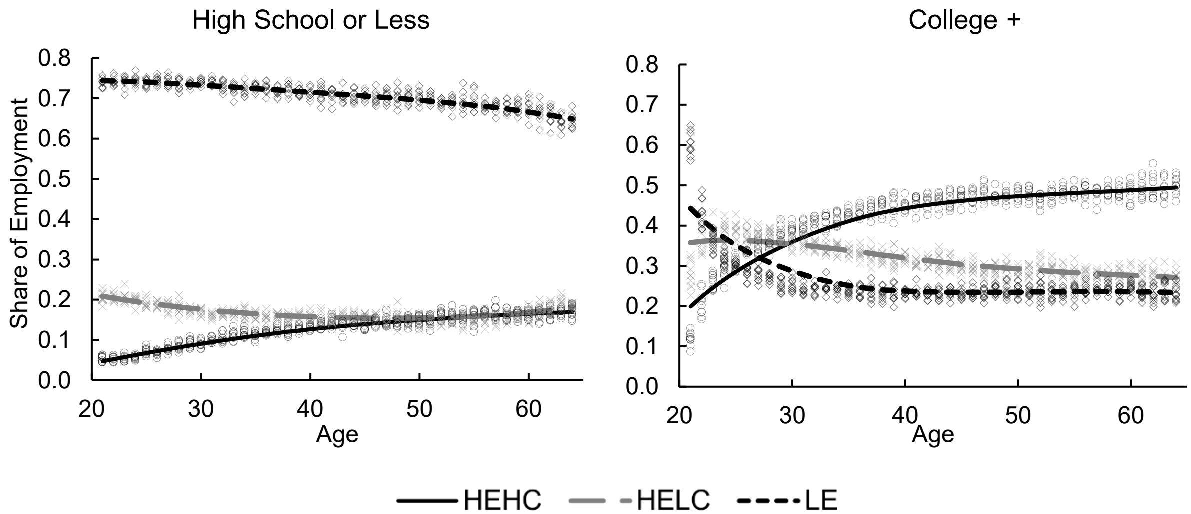


Figure 3. Employment shares in HEHC, HELC, and LE occupations by age and education, men only, 2010-2019

Note: The dots report the employment share for a given age-year observation between 2010-2019. The lines report the fitted values from locally weighted regressions. The sample includes male workers only. Occupations are grouped by exposure and complementarity based on the classifications of Felten et al. (2021) and Pizzinelli et al. (2023). HEHC = high-exposure and high-complementarity occupations, HELC = high-exposure and low-complementarity occupations, LE = low-exposure occupations.

Source: Authors' calculations using data from the Current Population Survey 2010-2019 (US Census Bureau 2010-2019).

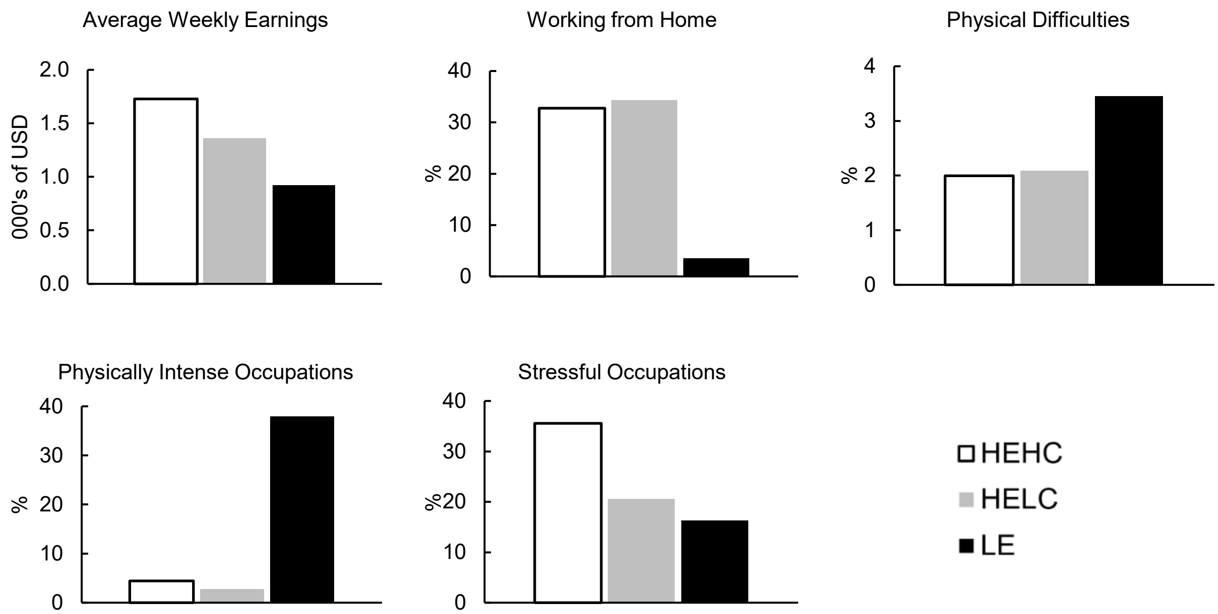


Figure 4. Job characteristics among occupation grouped by AI exposure and complementarity, men aged 55-69.

Note: The top left panel reports average weekly earnings over 2010-2019, in thousands of USD, adjusted to 2019 prices. The top center panel shows the share of workers who worked from home at least part of the time during the reference week over 2023-2024. The top right panel shows the share of workers who report having any physical difficulties over 2010-2019. The bottom panels show the share of workers who are employed in occupations that are 'physically intense' or 'stressful'. These definitions are based on O*NET scores for the work activity 'performing general physical activity' and the work style 'stress tolerance,' respectively, where the 75th percentile of each score across all occupations in the US SOC 2018 classification is used as a threshold. The sample includes male workers aged 55-69. Occupations are grouped by exposure and complementarity based on the classifications of Felten et al. (2021) and Pizzinelli et al. (2023). HEHC = high-exposure and high-complementarity occupations, HELC = high-exposure and low-complementarity occupations, LE = low-exposure occupations.

Source: Authors' calculations using data from the Current Population Survey 2010-2019 and 2023-2024 (US Census Bureau 2010-2019, 2023-2024), and O*NET (2023).

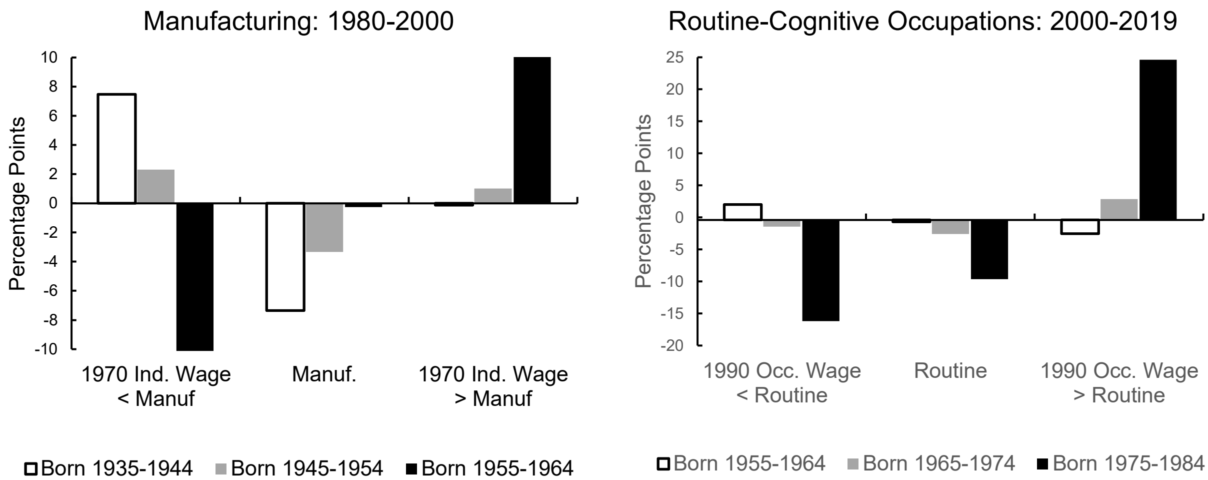


Figure 5. Changes in employment share by year-of-birth cohort across industries between 1980 and 2000 (left panel) and across occupations between 2000 and 2019 (right panel), men only.

Note: Each bar reports the change in the share of employment for a group of industries (left panel) or occupations (right panel) within the total employment of a given year-of-birth cohort of workers. In the left panel, the 4-digit NAICS industries are grouped based on whether in 1970 the mean wage was higher or lower than the mean wage of the set of industries in the manufacturing sector. In the right panel, the 4-digit occupations of the US Census 2010 classification are grouped based on whether in 1990 the mean wage was higher or lower than the mean wage in the set of occupations defined as routine cognitive by Cortes et al. (2020). Workers are grouped in year-of-birth cohorts of 10-year windows. The sample includes male workers only.

Source: Authors' calculations using data from the Decennial Census 1970, 1980, 1990, 2000, and the American Community Survey (US Census Bureau 1970, 1980, 1990, 2000, 2010, 2019).

Online Appendix: Replication of the chapter's main figures for women

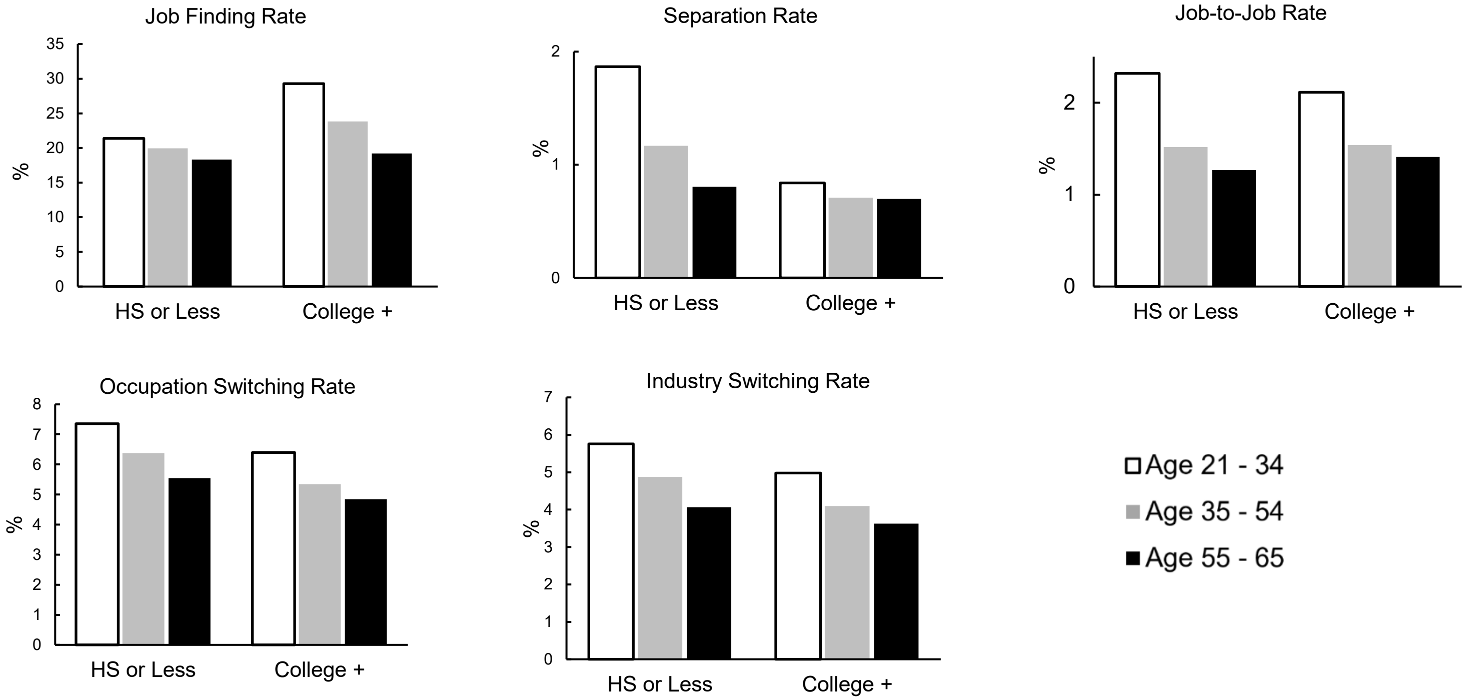


Figure A1. Indicators of labor market fluidity by age and education, women only, 2010-2019 averages.

Note: The top left panel reports the job finding rate for unemployed workers, defined as the probability of being employed in the following month. The top central panel reports the separation rate among employed workers, defined as the probability of being unemployed in the following month. The top right panel reports the job-to-job rate among employed workers, defined as the probability of working for a different employer in the following month. The bottom panels show the industry and occupation switching rates among employed workers, defined as the probability of reporting two different industries or occupations of employment across subsequent months. Industries are defined based on the 4-digit NAICS and occupations are defined based on the 4-digit Census classification. The sample include female workers over 2010-2019.

Source: Authors' calculations using data from the Current Population Survey 2010-2019 (US Census Bureau 2010-2019).

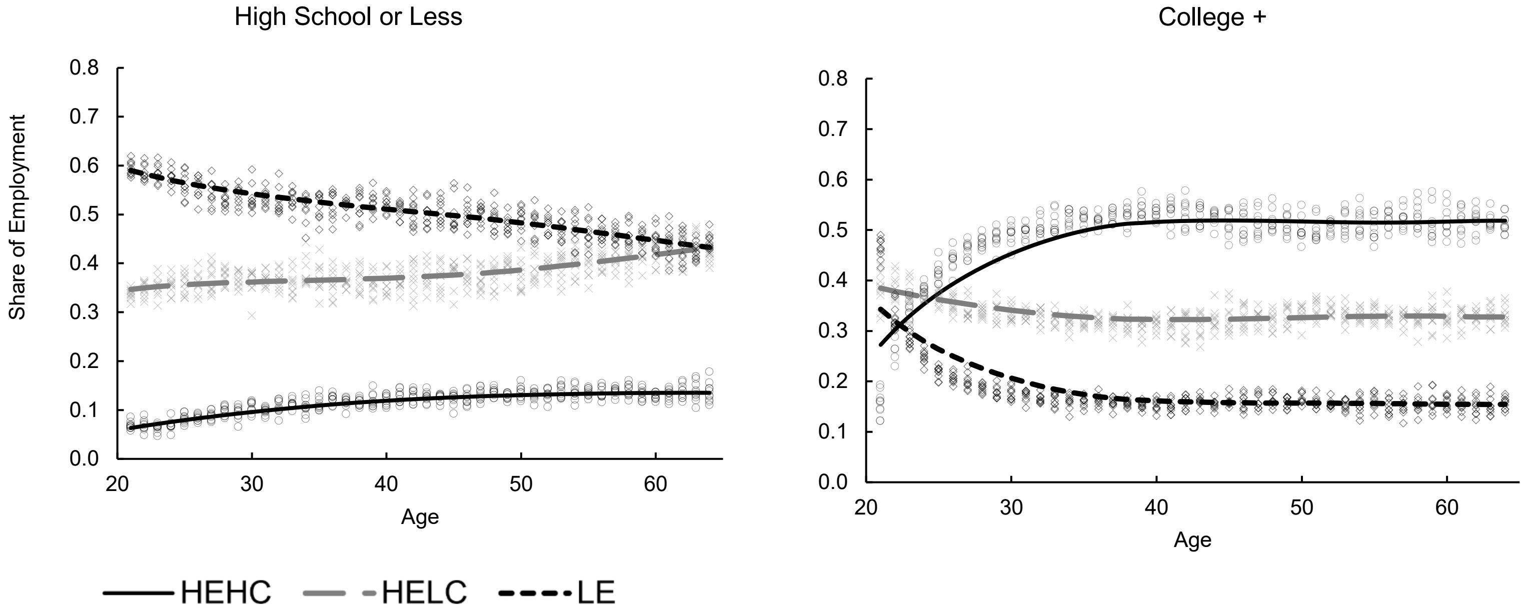


Figure A2. Employment shares in HEHC, HELC, and LE occupations by age and education, women only, 2010-2019

Note: The dots report the employment share for a given age-year observation between 2010-2019. The lines report the fitted values from locally weighted regressions. The sample includes female workers only. Occupations are grouped by exposure and complementarity based on the classifications of Felten et al. (2021) and Pizzinelli et al. (2023). HEHC = high-exposure and high-complementarity occupations, HELC = high-exposure and low-complementarity occupations, LE = low-exposure occupations.

Source: Authors' calculations using data from the Current Population Survey 2010-2019 (US Census Bureau 2010-2019).

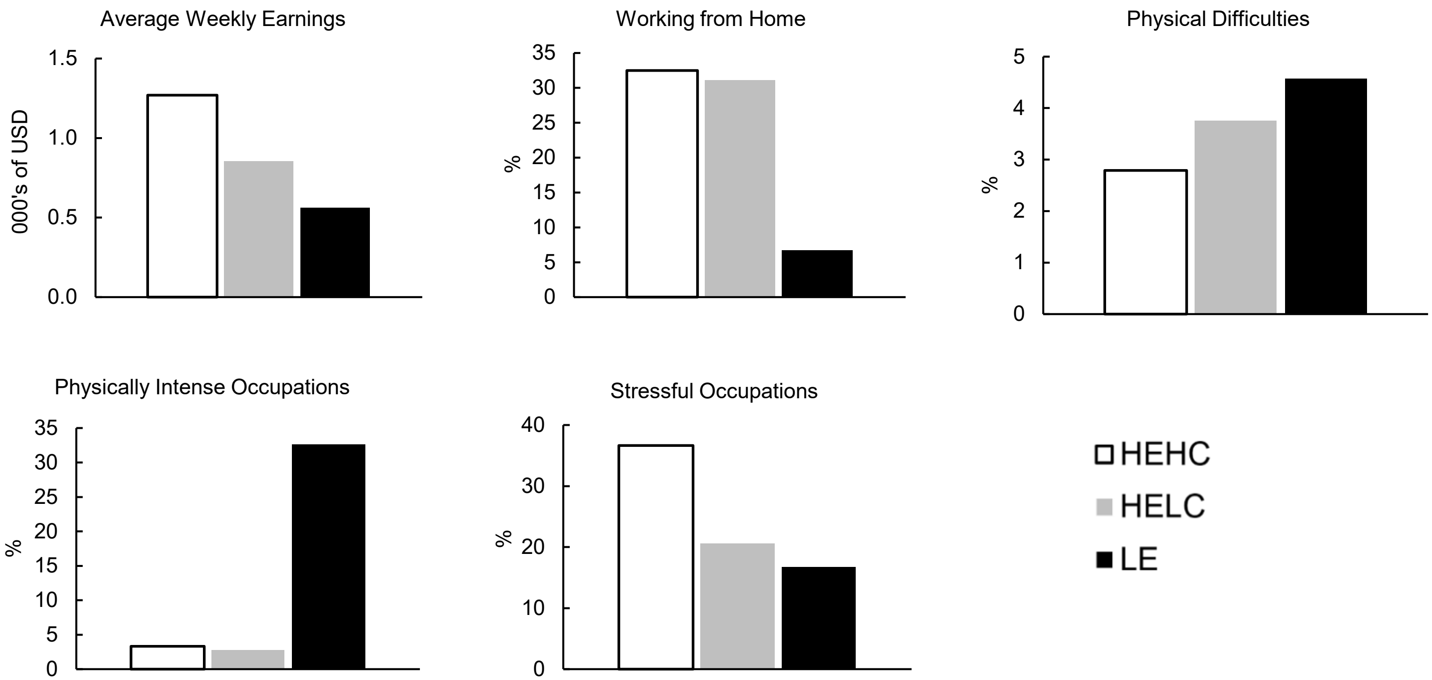
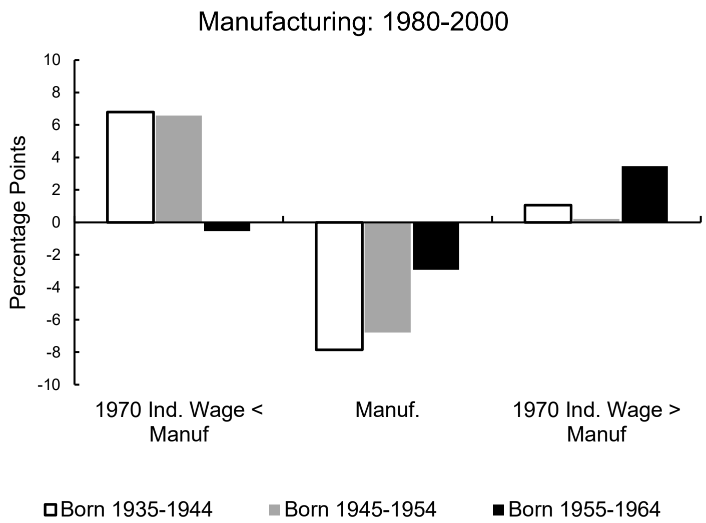


Figure A3. Job characteristics among occupation grouped by AI exposure and complementarity, women aged 55-69.

Note: The top left panel reports average weekly earnings over 2010-2019, in thousands of USD, adjusted to 2019 prices. The top center panel shows the share of workers who worked from home at least part of the time during the reference week over 2023-2024. The top right panel shows the share of workers who report having any physical difficulties over 2010-2019. The bottom panels show the share of workers who are employed in occupations that are ‘physically intense’ or ‘stressful’. These definitions are based on O*NET scores for the work activity ‘performing general physical activity’ and the work style ‘stress tolerance,’ respectively, where the 75th percentile of each score across all occupations in the US SOC 2018 classification is used as a threshold. The sample includes female workers aged 55-69. Occupations are grouped by exposure and complementarity based on the classifications of Felten et al. (2021) and Pizzinelli et al. (2023). HEHC = high-exposure and high-complementarity occupations, HELC = high-exposure and low-complementarity occupations, LE = low-exposure occupations.

Source: Authors’ calculations using data from the Current Population Survey 2010-2019 and 2023-2024 (US Census Bureau 2010-2019, 2023-2024), and O*NET (2023).



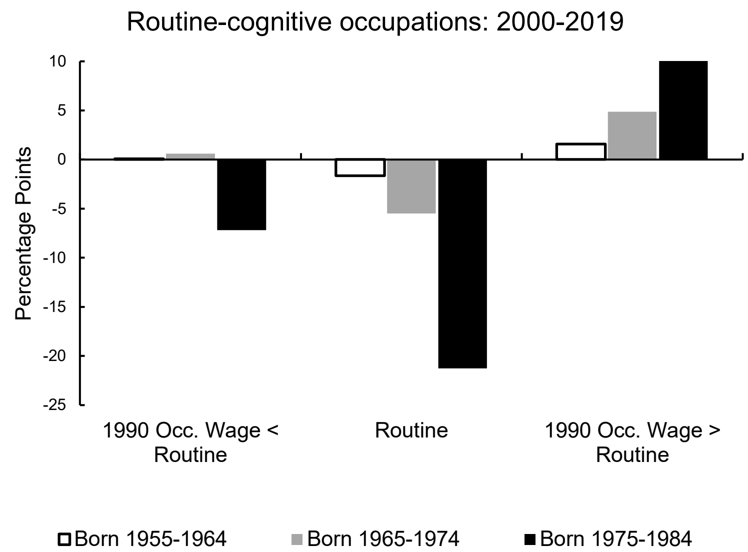


Figure A4. Changes in employment share by year-of-birth cohort across industries between 1980 and 2000 (left panel) and across occupations between 2000 and 2019 (right panel), women only.

Note: Each bar reports the change in the share of employment for a group of industries (left panel) or occupations (right panel) within the total employment of a given year-of-birth cohort of workers. In the left panel, the 4-digit NAICS industries are grouped based on whether in 1970 the mean wage was higher or lower than the mean wage of the set of industries in the manufacturing sector. In the right panel, the 4-digit occupations of the US Census 2010 classification are grouped based on whether in 1990 the mean wage was higher or lower than the mean wage in the set of occupations defined as routine cognitive by Cortes et al. (2020). Workers are grouped in year-of-birth cohorts of 10-year windows. The sample includes female workers only.

Source: Authors' calculations using data from the Decennial Census 1970, 1980, 1990, 2000, and the American Community Survey (US Census Bureau 1970, 1980, 1990, 2000, 2010, 2019).