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What the history of (new) jobs can tell us about the impact of technological change on employment

William Skoglund* Jakob Molinder[†] Kerstin Enflo[‡]

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Abstract

There is currently widespread concern that rapid technological change will fundamentally change the nature of work. In this paper we show that, despite 140 years of technological change, more than 70 percent of employment today is located in occupations whose core economic functions already existed in the late nineteenth century. Full-count Swedish census and administrative data from 1880 to 2019, harmonized to five-digit HISCO, let us observe how many people work in each occupation. This yields far greater occupational persistence than when new work is inferred from the appearance of new job titles. To characterize the new work that does emerge, we distinguish Schumpeterian occupations, tied directly to new technology, from Smithian occupations, arising from a deeper division of labor. Most new work is Smithian. Schumpeterian occupations, on the other hand, remain small and unstable, with an increasingly older workforce, and it is specialization, not technology or newness, that commands the largest earnings premium. Technology sustains employment less by expanding technological occupations than by creating the scale on which specialization depends.

JEL: J21, J24, O33, N33, N34, J16. **Keywords:** New work, occupational structure, technological change, division of labor, HISCO, long-run labor markets.

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1 Introduction

Recent technological change, particularly the rise of computerization and artificial intelligence, has renewed longstanding concerns of “technological unemployment”, a term famously defined by John Maynard Keynes (1930), or that automation may destroy jobs in high-risk occupations (Frey & Osborne, 2017; Georgieff & Milanez, 2021). But technology both destroys and creates. The question that matters for employment is therefore not simply whether technology destroys jobs, but where new work comes from, how much of it there is, and whether it pays.

The historical record speaks directly to this question, but the literature has yet to converge on how new work should be conceptualized and measured. Deming et al. (2025) document how successive waves of technological change have reshaped the occupational structure, grouping U.S. occupations into twenty broad categories that correspond roughly to the two-digit SOC codes used by U.S. federal agencies. They find, perhaps surprisingly, that the pace of occupational change has slowed over time, arguing that this comparative decline rather reflects how profound earlier shifts in occupational structure were. Their findings highlight the value of studying the occupational structure over long time horizons, since the emergence of new work and the reallocation of labor across occupations often unfold gradually.

At the opposite end of the spectrum of detail, Autor et al. (2024) identify “new work” in the U.S. labour market over 1940–2018 by comparing successive editions of the U.S. Census Alphabetical Index of Occupations and Industries. Tracing the appearance of new occupational micro-titles derived from Census respondents’ free-text job descriptions they argue that innovation creates new forms of labour demand not only by changing existing jobs but also by generating new job categories. On this basis, they conclude that the majority of current U.S. employment is in job specialties that have emerged since 1940, an inference that ultimately rests on the appearance of new job titles.¹

Taken together, the studies show that the debate has yet to settle on two main issues. The first is conceptual: what should count as new work depends on where the boundary of an occupation is drawn. At the level of broad occupational groups, only a major reorganization of economic activity registers as change; at the level of individual micro-titles, a new name for an enduring activity does. The second is empirical: establishing how much employment is located in new work requires measuring the number of workers in each occupation directly, something that is rarely observed continuously over long time horizons.

We contribute to this debate by tracing employment within occupations across nearly a century and a half. We draw on full-count Swedish censuses from 1880 to 1910, a sample from 1930, and administrative registers covering 1960–2019, which together provide near-universal population coverage. We harmonize all occupational information to five-digit HISCO (Leeuwen et al., 2002), providing a highly detailed view of the occupational structure with up to 600 distinct occupations. Because HISCO classifies occupations by function rather than title, an occupation registers as new when a new economic function appears in the labor market, rather than when an enduring function simply acquires a new name.² The breadth and detail of

¹A subsequent paper by Autor et al. (2026) uses newly available individual-level occupational write-ins from the 1940 and 1950 Census Complete Count files and confidential ACS data for 2011–2023, which means that they can instead match workers directly to these detailed titles. This direct measure produces considerably lower estimates: on their post-1970 window, whereas the title-share imputation implies that roughly one-third of contemporary workers are employed in new work, the person-level data put the share at about one-fifth.

²Whereas Autor et al. (2024) identify “new work” through the appearance of new occupational titles in the U.S. Census Alphabetical Index of Occupations and Industries, we instead analyze occupations through a threshold of employment in a harmonized, consistent, occupational classification. With about 600 distinct

the data allow us not only to identify new occupations but also to measure their actual employment weight rather than impute it. Linking HISCO codes to the census and register data further allows us to examine who works in these occupations, including their age and gender composition and how these characteristics change over time. Finally, income information available in the 1930 census and annually from 1970 to 2019 allows us to compare earnings across occupational groups in both the earlier census period and the modern register-data period.³

Although much of the literature approaches technological change through the tasks that make up an occupation (Acemoglu & Autor, 2011; Acemoglu & Restrepo, 2019; Autor et al., 2003), we take a different approach. Acknowledging that labor markets organize and reward occupations rather than tasks, we focus on occupations as our main unit of analysis. Wages, employment, and job survival are tied to occupations, not to the individual tasks workers perform. This matters especially in a long-run setting: tasks within a job may change over time, but occupations allow us to follow broader shifts in the labor market, including both the transformation of existing work and the emergence of genuinely new forms of economic activity. Studying technological change through the lens of occupations reveals two distinct ways in which innovation reshapes work. It may create genuinely new occupations, either directly through new technologies or indirectly as economic growth allows for finer specialization. Alternatively, technology may transform existing occupations without changing their underlying economic function: the carriage driver becomes a truck driver; the clerk begins to use a computer. Occupations may therefore be considerably more persistent than the tasks and technologies they contain⁴

Building on these patterns, we introduce a framework that distinguishes between *Schumpeterian* occupations, arising directly from technological change, and *Smithian* occupations, emerging through specialization and the division of labor. We operationalize this distinction using an LLM-based classification that assigns each occupation separate Smithian and Schumpeterian scores from 1 to 5. Since specialized technologies typically require a division of labor, Schumpeterian occupations will often also score highly on the Smithian dimension.

We document three main findings. First, most employment today are located in occupations that have existed for at least 140 years. The occupations occupying the largest share of employment in the occupations our approach is more detailed than the approach in Deming et al. (2025), who study long-run labor-market disruption by grouping U.S. occupations into 20 broad categories that roughly correspond to the two-digit SOC codes currently used by US federal agencies.

³The income data in the 1930 census are sourced from a combination of income declarations, tax registers, and employer records, capturing gross income from all sources for individuals earning above the tax threshold, which was set at 600 crowns in 1930. This threshold can be contextualized by considering the typical wages in 1930 for certain low-income groups: male agricultural laborers earned just over 1,000 crowns, while female servants in agriculture earned slightly less than 900 crowns. In contrast, male workers in a typical low-wage industry such as textiles and clothing earned more than 2,000 crowns, with women in the same sector earning just above 1,500 crowns. Even minors in this industry earned enough to be taxed, with incomes around 800 crowns. Wage information is derived from official wage statistics compiled by Statistics Sweden and digitized by the Historical Labor Database (HILD) project. As a result, in our data, more than 80 percent of men and 30 percent of women aged 20 to 60 have reported income. (Bengtsson & Molinder, 2024; Bengtsson et al., 2021)

⁴The second possibility connects to a growing literature that treats occupations not as collections of independently substitutable tasks but as bundles whose boundaries are costly to redraw (Autor & Thompson, 2025; Becker & Murphy, 1992; Garicano et al., 2026)—a literature partly motivated by evidence that AI shifts the task content of jobs more than it eliminates them (Eloundou et al., 2024; Humlum & Vestergaard, 2025).

modern economy —nursing, teaching, retail, transport, administration— are, in their economic function, the same occupations that organized work in the late nineteenth century, even as their task content has been transformed by technology. This finding is robust beyond the Swedish case: when we apply the same framework to the United States, we find a similarly persistent occupational structure, with the bulk of employment concentrated in historically incumbent occupations.

Second, this long-run persistence coexists with substantial occupational dynamism. Occupational churn rises over time, and workers increasingly move between occupations, even as the broader functional structure of employment remains relatively stable. This suggests that technological change often transforms how work is organized within existing occupational functions rather than simply replacing old occupations with entirely new ones. Consistent with this interpretation, Smithian occupations are more likely to survive over time, whereas Schumpeterian occupations are more volatile.⁵

Third, Schumpeterian occupations account for only a modest share of total employment, and their labor-market rewards are uneven. Their importance lies less in the number of workers they directly employ than in what they make possible elsewhere in the economy. Over time, the workers in Schumpeterian occupations are increasingly older. This suggests that new technological occupations do not necessarily function as broad entry points for younger cohorts. At the same time, highly specialized technological occupations earn substantial wage premia, while occupations that are as highly specialized but lack technological content see similar premia as their more Schumpeterian counterparts. This suggests that specialization is the driving factor behind earnings. Moreover, we observe no wage premium for occupations created in the 21st century. Instead, we argue that the content of occupations drive premia, not when they become new.

Together, these findings reframe the question of where new work comes from. Technological innovation remains central to long-run economic change, but its contribution to durable and well-paid employment operates primarily through the division of labor it enables rather than through the direct expansion of technological occupations themselves. The Schumpeterian sector is small but catalytic: it raises productivity and expands market scale, while the long-run growth of employment occurs mainly through Smithian specialization within persistent economic functions. Technology creates scale; scale creates specialization; specialization creates durable labor demand and premia.

The paper speaks to several literatures. First, we contribute to research on new work and occupational change (Autor et al., 2024, 2026; Lin, 2011) by showing that occupational persistence is substantially greater once occupations are studied as enduring economic functions rather than as evolving task bundles or occupational titles. We also contribute to the emerging literature on who performs new work. Autor et al. (2026) show that new work disproportionately employs younger and more educated workers and commands wage premia consistent with returns to scarce, specialized expertise. Relatedly, Autor and Dorn (2009) show that occupational decline is reflected in the age structure of employment, as declining occupations “get old” when younger workers cease to enter while incumbent workers remain. We extend this perspective over the long run by examining how workers in new and old occupations differ systematically by age, gender, and income, and how these differences evolve as new occupations emerge and older ones persist. Second, we add to the literature on technology and labor demand (Acemoglu & Restrepo, 2019; Autor & Dorn, 2013). By distinguishing between technological and division-of-labor mechanisms of occupational creation we show that specialization is an important source of new work. Third, we inform the literature on job multipliers

⁵The clearest historical case of technological occupational transformation is the rise and fall of second industrial revolution occupations, which were predominantly tied to manufacturing. At the height of Swedish industrial society, these occupations accounted for a substantial share of total employment—larger, in fact, than the share ever reached by occupations associated with the third industrial revolution.

and agglomeration (Moretti, 2010; Moretti & Thulin, 2013; Ostermeyer, 2023) by showing that the bulk of employment is located in occupations that are not directly related to new technological change, but rather appear in increased demand, specialization and the division of labor, while the technological sector remains small, but dynamic. Finally, we engage with the historical literature on occupational structure and economic development (Cockriel, 2024; Schneider, 2026; Vipond, 2024) by showing the persistence of old jobs despite several waves of technological disruption over more than a century.

1.1 Occupations

Following Durkheim (1984), we view occupations, not merely as collections of tasks performed by individuals, but as social and economic functions within a broader division of labor. Occupations describe the role that workers occupy in the organization of production: what kind of economic need they serve, how their work relates to other forms of work, and how labor is divided across society. This perspective differs from approaches that classify occupations primarily by social rank or class position. As M. B. Katz (1972) argues, occupations can be classified either according to social rank or according to their economic function, and these approaches capture fundamentally different aspects of social structure. We follow the latter approach. While stratification-based schemes are useful for studying status and social structure (Goldthorpe, 1987; Leeuwen & Maas, 2011; Wright, 1985), they are less suited for analyzing how the organization of production changes over time.

Thinking of occupations as functions also helps clarify what it means for work to change. Some economic functions are historically persistent: societies continue to need transport, trade, care, administration, construction, and communication. Yet the occupational forms through which these functions are carried out may change substantially. Existing functions may be divided into narrower specialties, combined with new forms of knowledge, or transformed by new technologies. In some cases, technological change creates entirely new functions. In others, it changes how old functions are performed.

Two mechanisms are particularly important. The first is increasing specialization. As markets grow, organizations become larger, and production becomes more differentiated, broad occupational roles may split into more narrowly defined occupations. This is the classic Smithian logic of the division of labor: the extent of the market makes finer specialization possible. The second mechanism is increasing complexity. As production systems, technologies, and organizations become more complex, the knowledge required to perform a function may expand. This raises the return to specialized expertise and encourages the emergence of new occupational roles. New technology affects both mechanisms. It can create new functions directly, but it can also deepen specialization within existing functions by increasing the complexity of production and coordination.

Chandler (1978)’s account of the transformation of commercial occupations illustrates this process. In the colonial economy, the general merchant “[...]ruled the economy” (Chandler, 1978, p. 17), performing a broad set of commercial functions. As the economy grew and markets became more complex, this general role was gradually split into more specialized occupations. Shopkeepers came to dominate retail trade, merchants specialized in particular goods, brokers acted as intermediaries in large ports, and financial institutions provided liquidity and credit. The core economic function of trade did not disappear. Rather, it was reorganized through a finer division of labor. New occupations emerged not because the underlying function was entirely new, but because scale, market integration, and organizational complexity created demand for

more specialized roles.⁶

1.2 Smithian or Schumpeterian?

We use the functional perspective to distinguish between two forms of occupational emergence: *Smithian* and *Schumpeterian*. By *Smithian* occupations, we refer to occupations that emerge primarily through increasing specialization, market expansion, and a more extensive division of labor (Chilosi et al., 2025). These occupations arise when existing economic functions are split into narrower roles as demand grows or as organizations become more complex. We illustrate this process of occupational splitting and specialization in Figure 1. Examples include brokers, accountants, personnel specialists, logistics workers, and other occupations that develop out of broader commercial, administrative, or organizational functions. Their emergence is not necessarily driven by a single new technology, but by the growing scale and complexity of economic activity.

By *Schumpeterian* occupations, we refer to occupations that are more directly tied to technological innovation. These occupations arise around new technologies, production methods, infrastructures, or forms of technical expertise. In the early twentieth century, the spread of electrification generated occupations related to electrical systems, electrical engineering, and electrical machinery. Later, computerization created occupations linked to software, data processing, and information technology. These occupations are Schumpeterian in the sense that they are connected to new technological paradigms and to the process of creative destruction.

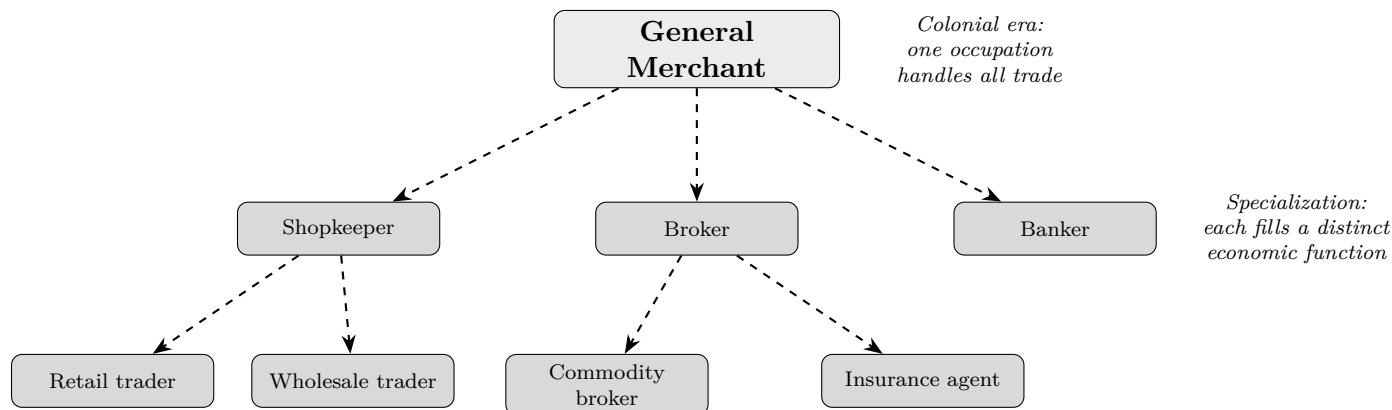
The distinction is analytical rather than absolute. Many occupations may be both *Smithian* and *Schumpeterian*. In fact, successful technological change often generates further specialization. New technologies create new bodies of knowledge, new coordination problems, and new complementary activities. Becker and Murphy (1992) provide the mechanism that links the two. In their account, the degree of specialization is governed less by the extent of the market, as in Smith, than by the growth of knowledge and the cost of coordinating specialists who perform complementary tasks. As the knowledge required to perform a function well expands, the returns to concentrating on a narrower set of tasks rise, and broad roles divide into finer specialties—so long as coordination costs do not rise faster than the gains from the finer division of labor. Their own examples are instructive: engineering was a largely undifferentiated occupation in the early nineteenth century, but the accumulation of scientific and technical knowledge split it into civil, mechanical, electrical, chemical, and automobile specialties, each acquiring its own professional society over the following century. Medicine followed the same path, with the share of specialists among U.S. physicians rising from a small minority in the nineteenth century to a large majority today. In both cases, new technologies and new knowledge did not simply create new functions; they also increased the payoff to specialization within existing functions.

This distinction matters for how we expect occupations to evolve over time. Occupations that are primarily *Schumpeterian* may be more dynamic but also more vulnerable to technological obsolescence. Skills tied closely to a particular technology may depreciate quickly when that technology is replaced. The decline of punch-card operators after the spread of modern computing illustrates this logic. By contrast, occupations

⁶The importance of occupational functions has also been emphasized in the geography literature. Duranton and Puga (2005) develop a model centered on the functions performed by workplaces and workers, arguing that clustering by occupational function may be more meaningful than clustering by industrial sector. More recently, Henning and Boström Elias (2026), drawing on Stabell and Fjeldstad (1998), group occupations according to their position within the production process.

that are primarily *Smithian* may be more persistent because they are rooted in enduring economic functions, even if their task content changes. A broker, accountant, administrator, or logistics worker may use very different tools over time, but the underlying function may remain.

Figure 1: Division of Labor Through Functions

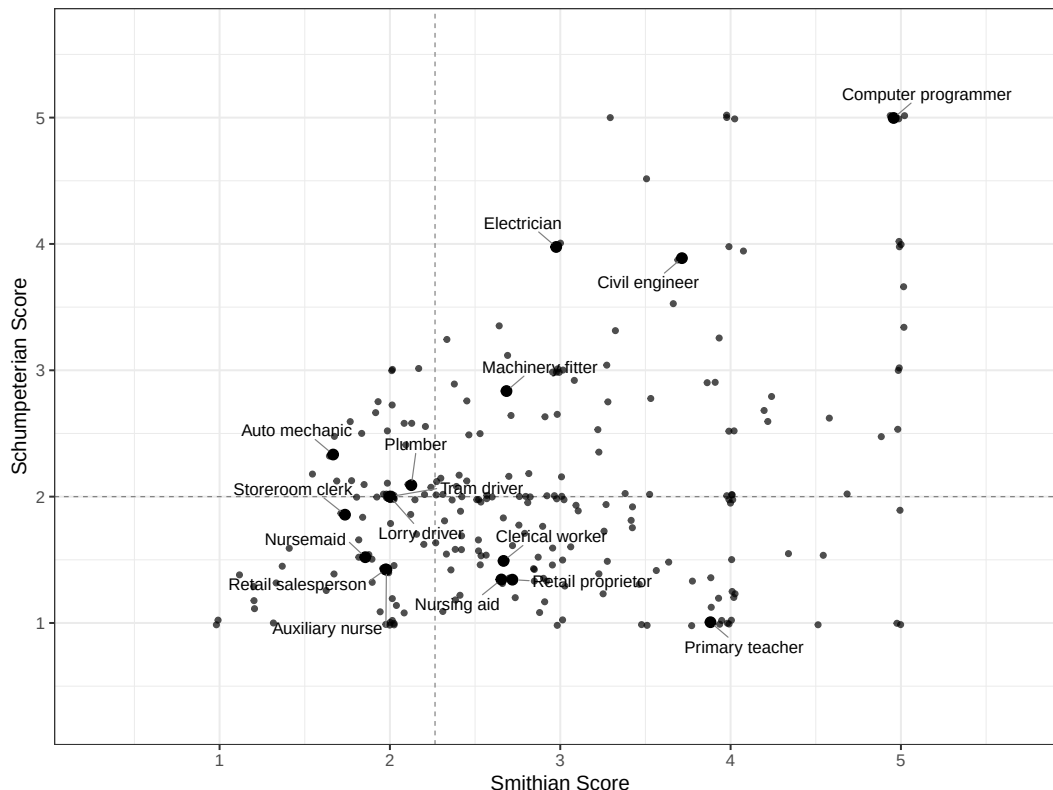


Note: Illustrative diagram of Smithian job creation through division of labor, following Chandler (1978)’s example of the colonial-era general merchant. *Source:* Authors’ illustration.

To observe Smithian and Schumpeterian job creation, we code each occupation in our data according to their technological intensity. This is done using a *fewshot* approach, prompting an LLM. In Appendix C we discuss this coding in detail and show that more Schumpeterian jobs are semantically linked to bundles of technological words. Each occupation receives a score from 1-5 as to how *Smithian* or *Schumpeterian* it is. Almost by definition, Schumpeterian jobs will also score highly on being smithian as a pre-requisite for the use of new and specialized technology is a division of labor. In Figure 2 we show the distribution of smithian, and schumpeterian scores for 2019, labelling the four most-common occupations per quadrant (quadrants defined by the global median of time-averaged scores).

Occupations in the top-left quadrant, high-schumpeterian and low-smithian include jobs that are tied to a technology but which tend to fulfill basic functions in society. These are drivers (i.e. Tram and Lorry drivers), Auto mechanics and plumbers. Conversely, the top-right quadrant, occupations that are high-high, include electricians, civil engineers, machinery fitters and computer programmers. The low-schumpeterian quadrants instead contain teachers, clerks, proprietors and nurses. The main difference between the bottom left and bottom right quadrants is the degree of specialization. Auxiliary nurses end up being low-smithian as they represent a general nurse role. Nursing aids, by comparison, represent a subdivision of the nursing role and thereby a greater division of labor.

Figure 2: Smithian vs. Schumpeterian Occupational Scores (2019)



Note: Each point is a 5-digit HISCO occupation observed in 2019, plotted at its time-averaged Smithian (x-axis) and Schumpeterian (y-axis) scores. Dashed lines mark the cross-occupation medians (Smithian = 2.33, Schumpeterian = 2.00), defining the four quadrants. Labels show the four most-common occupations by 2019 employment in each quadrant. *Source:* LISA 2019; scores from the classification in Figure A10.

1.3 Technological waves, job creation and renewal

Whether technology augments existing occupations with novel tasks or gives rise to entirely new ones, both forms of occupational change are closely tied to long-run processes of structural transformation. Economic historians have often understood these processes as unfolding in historical waves associated with major technological breakthroughs and changing international market conditions, which we outline in the rest of this section.

Building on the idea of General Purpose Technologies (Bresnahan & Trajtenberg, 1995) and Dahmén’s concept of “development blocks” (Dahmén, 1950, 1988), we will present our results broadly organized by technological waves. This reflects our notion that technological change is a broader systems of complementary innovations that reorganize production and generate new demands for labor, infrastructure, and specialization. Below is an overview of each wave and its potential impact on job creation and renewal.

The first industrial revolution saw its large-scale breakthrough in Sweden around the mid-nineteenth century, considerably later than the emergence in England. As a late-comer, Swedish economic development was shaped by export-oriented production in raw materials such as timber, iron, and agricultural products, particularly oats, driven by expanding international trade opportunities (Jörberg, 1973; Schön, 2012). Figure 3 shows that the division of labor was typical for that of a peripheral economy specialized in agriculture

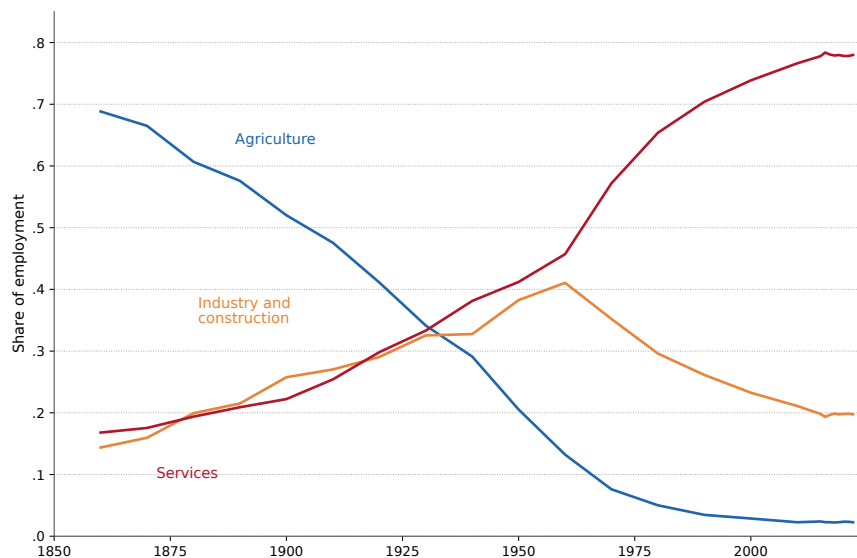
and raw material exports: around 1880 around sixty percent of the employment was occupied in agriculture (estimated from Schön and Krantz (2015): the Swedish Historical National Accounts). We therefore refer to the occupations present in the 1880 and 1890 census as *incumbent jobs*.

The second industrial revolution was characterized by a swarm of complementary innovations whose diffusion accelerated from the 1890s onwards, with electricity, the combustion engine, new steel technology, organic chemistry, and modern communications at its core. In Sweden, the electrification of industry became the central kernel of two partly overlapping development blocks: one organized around metal, metal goods, machinery and railways, and another around chemistry, pulp and paper (Enflo et al., 2008). The growth effects of these technologies operated through several reinforcing channels: new engines in land and sea transportation enabled deeper market integration, specialization, and economies of scale; a growing stock of machinery augmented the motive power at workers' disposal; electrification permitted a more efficient organization of production through group- and unit-drive; and the new technologies entailed strong skill-technology complementarities, particularly in the production and use of electro-technical equipment (Goldin & Katz, 1998). The new occupations reaching the threshold in the 1900-1930 censuses are referred to as *second industrial revolution jobs* and coincide with an expansion of employment into the industrial sector, shown in Figure 3.

The third industrial revolution, also described as the ICT revolution, organized around microelectronics, the computer, and digital telecommunications unfolded between roughly 1960 and 2000. The ICT revolution proved strongly skill-biased, raising the relative demand for educated workers and accelerating the long-run trend of skill-biased technical change (Goldin & Katz, 1998; L. Katz & Margo, 2014; L. Katz & Murphy, 1992). In Sweden, (Schön, 2010) dates the breakthrough of the new development block around microelectronics and computers to the structural crisis of the 1970s, after which the industrial structure shifted away from traditional resource-based industries and toward knowledge-intensive manufacturing and producer services. Figure 3 shows a sharp increase in service employment, simultaneously as the industrial jobs started to decline. The occupations emerging in the 1960-1990 are referred to as *third industrial revolution jobs*.

A fourth wave of technological change has been unfolding since around 2000, driven by digital platforms, machine learning, and most recently generative artificial intelligence as a new general purpose technology with broad potential to automate cognitive tasks (Acemoglu & Restrepo, 2020; Brynjolfsson et al., 2021). In contrast to earlier waves, this period has been characterized by job polarization—employment growth concentrated at the top and bottom of the wage distribution, with a hollowing-out of routine middle-skill occupations (Autor & Dorn, 2013)—and by a slowdown in aggregate productivity growth that has prompted debates about secular stagnation and the limits of recent innovation relative to the transformative technologies of the past (Gordon, 2016; Summers, 2014). The occupations in the 2000-2019 data are labeled *21st century*, given that it is still too early to tell whether the latest transformations can be labeled a fourth industrial revolution.

Figure 3: Shares of Employment by Sector, Sweden 1860–2022



Note: Shares of total employment in agriculture, industry and construction, and services. Services exclude unpaid domestic work. *Source:* Schön and Krantz (2015), Swedish Historical National Accounts, and SCB official statistics for recent years.

2 Data

Before turning to the formal analysis, it is useful to clarify terminology and describe our data. We use the term “occupation” to refer to a job title, that is a specific HISCO-coded category such as *general farmer* or *nurse*. The term “job” instead refers to the employment structure, that is, the number of people working in each occupation. A new job is created when a new occupational title enters the labor force and subsequently expands; we operationalize this as the first census or registry year in which a unique 5-digit HISCO code reaches a threshold of 50 workers.⁷

We assemble individual-level data spanning nearly a century and a half. For the historical period we draw on the full-count censuses of 1880–1910 together with the partially digitized 1930 census; for the modern period we use administrative registry data covering 1960–2019.⁸ The Swedish data landscape is distinctive in its near-universal coverage of individuals, allowing us both to trace the occupational titles in use at each point in time and to directly observe employment within them.

To compare occupations consistently across this period, we harmonize all codes to HISCO, the scheme we discuss at length below. The 1880–1930 censuses contain simple occupational strings which we code to HISCO using a crosswalk. Prior to this we standardize occupational strings, cleaning up abbreviations and typos. We then join the standardized strings to HISCO using a simple join, and a fuzzy-match for

⁷To assess the sensitivity of this 50-worker threshold, we vary it in Figure A3; for most normal-range thresholds the changes do not qualitatively affect our results or the long-run trends reported in Figure 6. Only when we employ an extremely large definition of new jobs, that is twenty times the baseline, do we observe a change to the core result. Yet, even with such a large definition, only a minority of present employment is located in occupations created after 1960.

⁸For 1960–1990 we rely on the *Folk- och Bostadsräkning* (FOB); thereafter we draw on the LISA database, which covers all individuals aged 15 and above.

occupational titles that we cannot match.⁹ For the modern period we link the existing occupational codes in the 1960, 1970, 1980, and 1990 censuses, and the four-digit SSYK codes in the 2001 and 2019 registry data, to HISCO, using the OccCANINE model of Dahl et al. (2024) supplemented by manual coding.

To identify the emergence of new jobs, we follow Autor et al. (2024) and compare occupations between t and $t - n$. Having coded occupations to HISCO, we count occurrences by year and treat an occupation as a candidate new job in year t if no earlier period reached the 50-worker threshold.¹⁰

In Section 4.3 we exploit the income information contained in the 1930 census, together with modern registries from 1970 onward, to gauge the income premium associated with different jobs. The two sources differ in two respects. First, the modern registry data reports a range of incomes, the 1930 census simply reports total income. As a robustness, we consider different forms of income from 1970 onward in Figure A8 and found no systematic differences. Second, the sources differ in coverage: the 1930 income figures derive from taxation assessments and record positive income only for individuals above the contemporary income-tax threshold, 600 SEK, whereas the registries report earnings for the full population.

2.1 HISCO

HISCO, the Historical International Standard Classification of Occupations, fits our purpose of analyzing how occupations persist, specialize, and reorganize as economies develop. Modeled on the International Labour Organisation’s ISCO68 scheme, it was created to make occupations comparable across countries and over time (Leeuwen et al., 2002), and has since become the standard for coding occupations in historical settings.

Crucially, HISCO is detailed enough to register novelty. It resolves to roughly 600 hundred unit groups in our data, including categories tied to information technology such as *computer programmer* and *data manager*, as well as occupations linked to electricity, punch-cards, and other technologies of the early twentieth century. It also captures newer service roles such as *personnel specialists* and *aircraft cabin attendants*. The scheme therefore records genuinely new occupations as they emerge, while abstracting from shifts in the specific tasks a given occupation performs. This lets us focus on the underlying economic function an occupation fulfills—which tends to be more stable, and less sensitive to semantic changes in job titles, than the titles themselves.¹¹

The Swedish censuses are digitized and available in IPUMS. These censuses come with IPUMS’ HISCO-coding. However, we use Swedpops scheme and re-code the IPUMS data using the *OCCSTRNG* variable. For the registry data we use Dahl et al. (2024) and then manually check all occupations.¹² For the 1880–1910 censuses, 14 of 20 million individuals receive a HISCO code. Figure 4 summarizes our pipeline for coding occupations to HISCO and identifying new ones.

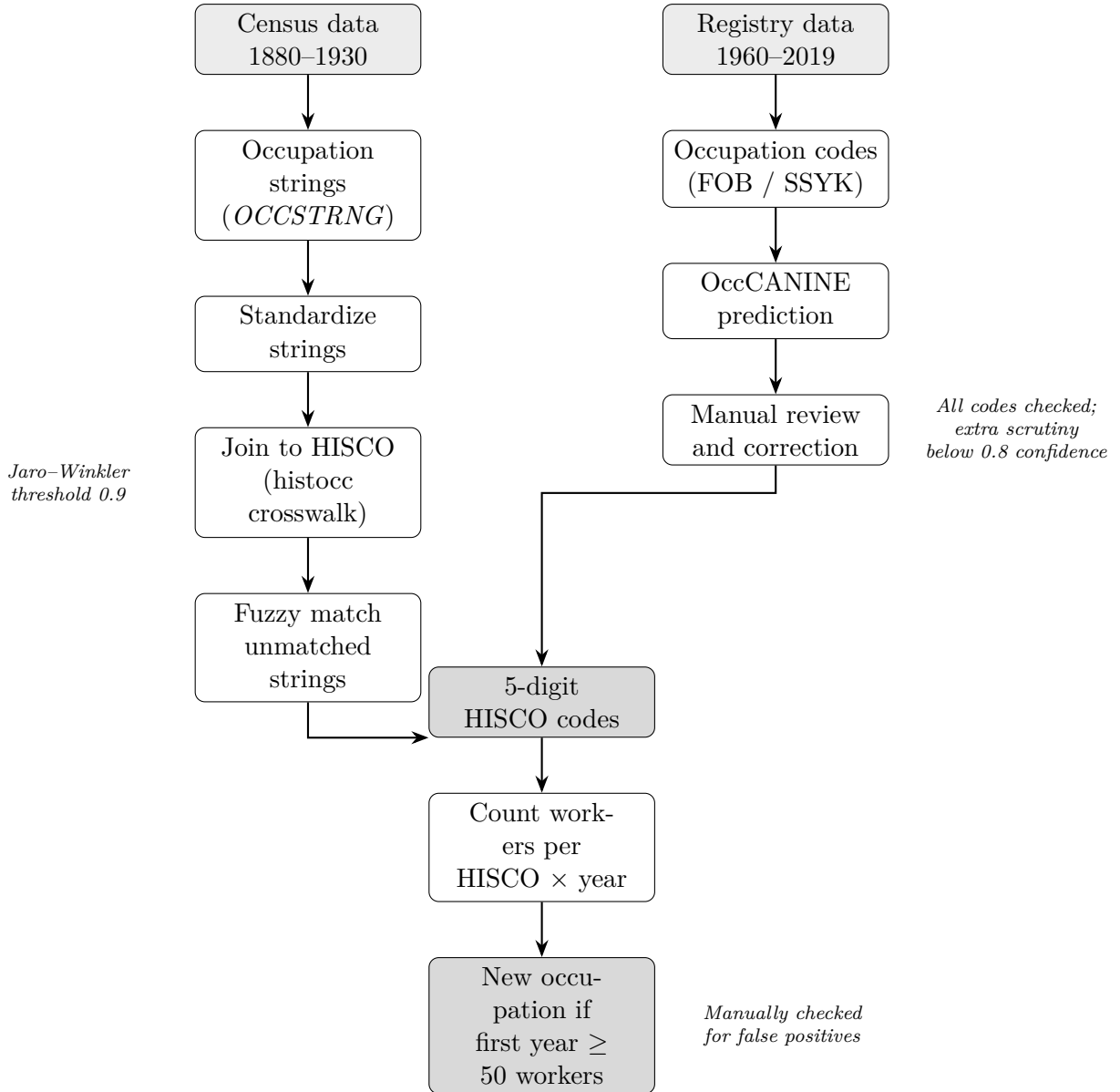
⁹We use the *histocc* package (Skoglund, 2025), fuzzy-matching using jaro-winkler and a threshold of 0.9 for matches.

¹⁰50 individuals is approximately 1 in 100,000 of the Swedish population at the time of our first census (1880). Because only half the 1930 census is digitized we multiply the occupational counts by two for that year.

¹¹This differs from the title-based approach in, for example Autor et al. (2024), which intentionally captures the emergence of new task specializations and occupational titles. Their more granular methodology is well suited for identifying new expertise domains, while our functional approach is better suited for studying long-run occupational persistence and structural change.

¹²We take special care to check the suggested codes below a confidence threshold of 0.8, however, all codes are looked at.

Figure 4: HISCO Coding Pipeline



Note: Pipeline for mapping historical census strings (1880–1930) and modern occupational codes (1960–2019) to 5-digit HISCO. Historical strings use the `histocc` crosswalk with Jaro–Winkler fuzzy matching; modern codes use OccCANINE (Dahl et al., 2024) with manual verification. *Source:* Authors’ illustration.

For the modern registry data, there are between roughly 300 and 450 occupational codes. Because these are not always unique occupations, but rather occupational groups, coding into HISCO can sometimes be ambiguous. In the 1960–1980 classifications, we have cases such as “*Economist, statistician*”. HISCO codes economists and statisticians separately. In these cases, we typically select the first occupation, unless more information is available.¹³

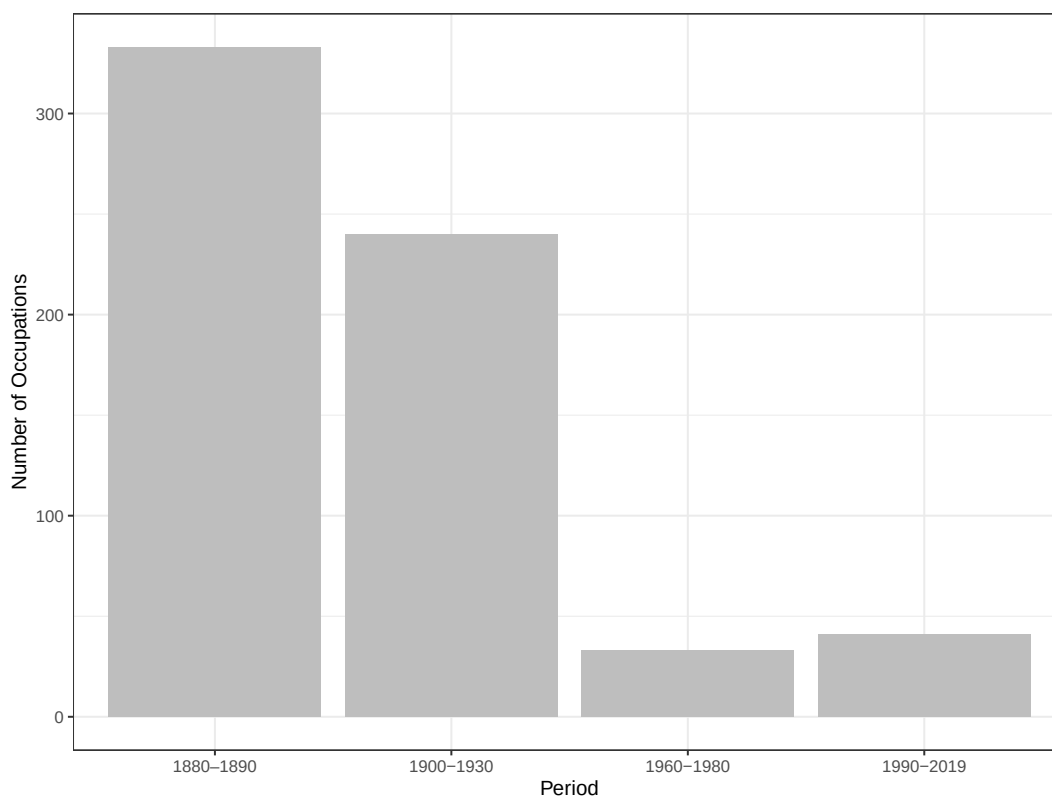
¹³This problem is not solvable using three-digit codes, as Statistician (08110) and Economist (09010) only share the same first digit.

3 The Occupational Structure in the Long-Run

3.1 Occupations and jobs

A first glance at our data shows that a little more than half of all occupations in our data were already present in 1880-1890. Figure 5 shows the number of harmonized 5-digit HISCO coded occupational titles on the y-axis and a division corresponding to the technological waves on the x-axis. Most new harmonized titles, about 240, were added during the second industrial revolution. Thereafter, the addition of titles have slowed down.

Figure 5: New occupations by technological wave



Note: Count of unique 5-digit HISCO codes that first reach the 50-worker threshold in each census or registry year. *Source:* IPUMS 1880–1910; Swedish 1930 census (50% sample); FOB 1960–1990; LISA 2001–2019.

Table 1: Most Common Occupations by Period and Year

YEAR	Incumbent	second industrial revolution	third industrial revolution	21st century
2019	Auxiliary Nurse (367565), Retail Trade Salesperson (241301), First-Level Education Teacher (206340)	Other Waiters, Bartenders and Related Workers (89774), Other Motor-Vehicle Drivers (77587), Electrician, General (77524)	Computer Programmer (152596), Industrial Relations and Personnel Manager (47780), Social Worker, General (47509)	Other Special Education Teachers (40839), Personnel Specialist (40774), Receptionist, General (27023)
1990	Auxiliary Nurse (322494), Office Clerk, General (260778), Machinery Fitter or Machine Assembler, Type of Machine Unknown (192288)	Buyer (115209), Electrician, General (57823), Other Waiters, Bartenders and Related Workers (53338)	Salesperson, Wholesale or Retail Trade (131435), Electrical Engineering Technician, General (63944), Social Worker, General (54794)	NA
1960	General Farmer (194656), Factory Worker (108928), Office Clerk, General (105858)	Other Machinery Fitters, Machine Assemblers and Precision Instrument Makers (except Electrical) (60547), Electrician, General (40220), Cabinetmaker (39524)	Salesperson, Wholesale or Retail Trade (150615), Electrical Engineering Technician, General (20441), Military, Specialisation Unknown (17320)	NA
1930	General Farmer (423362), Farm-Worker, General (288784), House Servant (105630)	Spinner, Weaver, Knitter, Dyer or Related Worker, Specialisation Unknown (14636), Excavator, Specialisation Unknown (9080), Cabinetmaker (5936)	Commercial Artist (48), Well Digger (46), Insurance, Real Estate or Securities Salesmen, Specialisation Unknown (44)	Other Engineering Technicians (42), Aircraft Engine Mechanic, Specialisation Unknown (32), Telecommunications Technician (28)
1910	General Farmer (313015), Farm-Worker, General (193068), House Servant (109513)	Spinner, Weaver, Knitter, Dyer or Related Worker, Specialisation Unknown (3997), Electrician, General (1940), Dairy Farm Worker, General (1573)	Insurance, Real Estate or Securities Salesmen, Specialisation Unknown (49), Electrical Engineering Technician, General (46), Other Sculptors, Painters and Related Artists (23)	Theatrical Producer (32), Translator (27), Statistician, General (19)
1890	General Farmer (244409), House Servant (179826), Other Military Ranks (117340)	Estate Agent (49), Metal-Press Operator (48), Supervisor and General Foreman (Manufacturing of Machinery and Metal Products) (45)	Other Sculptors, Painters and Related Artists (14), Hoisting Equipment Rigger, General (4), Insurance Clerk (1)	Statistician, General (14), Theatrical Producer (12), Other Clerical Supervisors (7)

Note: Table displays the three most-common occupations in each wave for each year, with employment counts in parentheses. Waves are defined by the year a HISCO code first reaches 50 workers: 1930 counts have been doubled to compensate for the 50% sample. “NA” indicates that the wave does not yet have any qualifying HISCOs in that year. *Source:* IPUMS 1880–1910; Swedish 1930 census (50% sample); FOB 1960–1990; LISA 2001–2019.

To get a sense of which new occupations were created and which persisted Table 1 reports the top occupations within each technological wave discussed in Section 1.3. The table highlights two patterns. The first is the striking long-run persistence of incumbent occupations, which dominate the employment structure throughout the period. General farmers (code: 61110) form the single largest occupation from 1890 until 1960, and while they no longer rank among the top occupations in 2019, they remain a substantial group. Other incumbent occupations follow a very different trajectory: house servants (code: 54020), one of the leading codes between 1890 and 1930, virtually disappear by the turn of the twenty-first century. By 2019, the largest occupational groups are still drawn from the incumbent pool, but their composition has shifted decisively away from primary production toward services—nurses (code: 07210), working proprietors (code: 41030), and teachers (code: 13320) now dominate.¹⁴ In 1960, by contrast, most of the leading incumbent occupations were still tied to production or agriculture.

The second pattern is that each technological wave generated distinctive new occupations, although the nature of these occupations differed markedly across waves. The second industrial revolution produced occupations tied to industrialization, mechanization, electrification, and modern transport, including spinners, weavers, knitters and dyers, machinery fitters, cabinetmakers, excavators, electricians, and later lorry and van drivers. The third industrial revolution generated a different set of occupations, associated with computers, administration, welfare services, and the knowledge economy, including computer programmers, electrical engineering technicians, personnel specialists, industrial relations and personnel managers, social workers, and sales workers. The 21st century wave added occupations such as special education teachers, receptionists, and automatic data-processing machine operators.¹⁵

Having mapped occupations onto the technological waves, we now turn to jobs—that is, to how many people actually work in occupations created each technological wave and how their weight in the employment structure has evolved over time. Figure 6 plots the share of total employment by the vintages: incumbent, second industrial revolution, third industrial revolution, and 21st century. The most striking pattern is that the majority of people continue to work in incumbent occupations. Despite successive waves of technological change, the bulk of the Swedish employment structure remains anchored in occupations that already existed before the second industrial revolution. The second most striking pattern is the rise and fall of second industrial revolution occupations, which are predominantly tied to manufacturing. At the height of Swedish industrial society, these occupations accounted for a substantial share of total employment—larger, in fact, than the share held by third industrial revolution occupations at any point in our data. The contrast with the third wave is instructive: occupations that first appear in relation to the third industrial revolution turn out to be the least impactful in employment terms. They reach a peak of around eight percent of employment in 1960 and have steadily declined into the twenty-first century. In Appendix C.2 we ask whether this stable employment structure is an artifact of HISCO by using the contemporaneous scheme used from 1960 to 1990 and show that this scheme shows similar persistence.

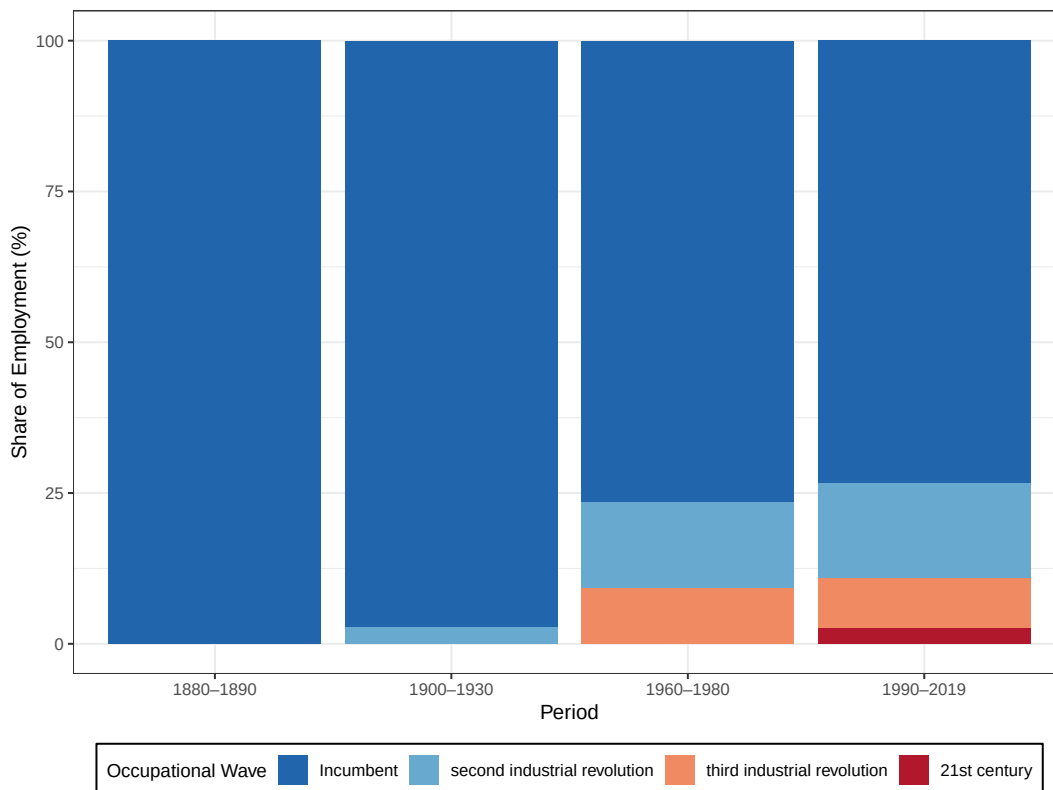
Importantly, the third industrial revolution occupations that do persist are not manufacturing-related.

¹⁴HISCO code 13320 refers specifically to first-level education teachers.

¹⁵Only some of these new occupations, however, became large enough to rank among the leading occupations by 2019. Among second-industrial-revolution occupations, waiters and bartenders, lorry and van drivers, and electricians remained among the largest groups. Among third-industrial-revolution occupations, computer programmers, industrial relations and personnel managers, and social workers had become the most important in employment terms. By contrast, the largest 21st century occupations—special education teachers, receptionists, and automatic data-processing machine operators—remained much smaller than both the dominant incumbent occupations and the largest surviving occupations from earlier technological waves.

As Table 1 shows, the occupations from this wave that retain employment weight are concentrated in services and the knowledge economy—computer programmers, personnel managers, and social workers—rather than in the production-side activities that defined the earlier technological wave.

Figure 6: Occupational Structure by Period and Technological Wave 1880-2019



Note: Share of total employment by occupational wave, in four 30-year periods. Waves are defined by entry year: Incumbent (before 1900), second industrial revolution (1900–1930), third industrial revolution (1960–1990), 21st century (post-2000). 1930 counts doubled (50% sample). *Source:* IPUMS 1880–1910; Swedish 1930 census (50% sample); FOB 1960–1990; LISA 2001–2019.

3.1.1 Comparison with the U.S.

One concern is that our findings may somehow be specific to the Swedish context. The process of job creation could potentially differ in a small, open economy, such as Sweden, compared to a larger and more dominant economy, such as the United States, might exhibit more extensive new job creation. To mitigate this concern we replicate our HISCO-based approach for the United States using microdata from the 1940 U.S. Census and the 2019 American Community Survey, obtained from IPUMS (Ruggles et al., 2025), and code U.S. occupational information into HISCO using OccCANINE. To this end, we obtain microdata from the IPUMS 1940 1 per cent sample and the American Community Survey of 2019. We code the occupations into HISCO following the approach outlined in Figure 4.

This exercise allows us to get an understanding for which U.S. HISCO-coded occupations observed in 2019 that were already present in 1940. We present the results in Appendix Figure A9. Specifically, in the U.S. data, we identify 36 occupations as new since 1940 out of 156 HISCO codes observed in 2019, but these new occupations account for only around 9 per cent of total employment. See details in Appendix B.

Thus, we find, similar to our findings for Sweden, that a substantial portion of U.S. employment today is in historically incumbent occupations. These findings give external validity to our findings for Sweden.

The persistence of incumbent jobs however stand in contrast to recent U.S. findings that a majority of current employment is in new job specialties introduced since 1940, by Autor et al. (2024) who use a title based approach. However, an important distinction between our approach and Autor et al. (2024) is that they cannot observe the number of people actually employed in the new occupations. Instead, their approach imputes employment in new work from the share of newly introduced detailed titles within broader Census occupations following the Lin (2011) approach.

In a recent study, Autor et al. (2026) do however use data from the newly available 1940 and 1950 Census Complete Count files and confidential American Community Survey data from 2011-2023, to add information about the number of workers actually employed in each job in 1940 and 1950. This shift from title shares to person-level employment measurement yields a larger role for old or incumbent occupations than the results in Autor et al. (2024). For example, they find that 7.2 per cent of workers in 1950 were employed in new work introduced after 1930, and that 18.3 per cent of workers in 2011-2023 were employed in jobs introduced since 1970. Thus, while Autor et al. (2026) continue to identify substantial new work, their person-level evidence implies a more persistent occupational structure than suggested by the title-based estimates in Autor et al. (2024) bringing their results closer to ours.

3.2 Occupational Churn

The dominance of incumbent occupations does not imply that the same occupations hold steady—the re-ordering documented in table 1, with general farmers and house servants giving way to nurses, proprietors, and teachers, already shows that the incumbent pool is reshuffled extensively even as its overall weight persists. Aggregate persistence and underlying turnover are therefore not in tension: the former can mask the latter. To see how much reshuffling actually takes place within and across categories, we need a measure of the flows, not just the levels.

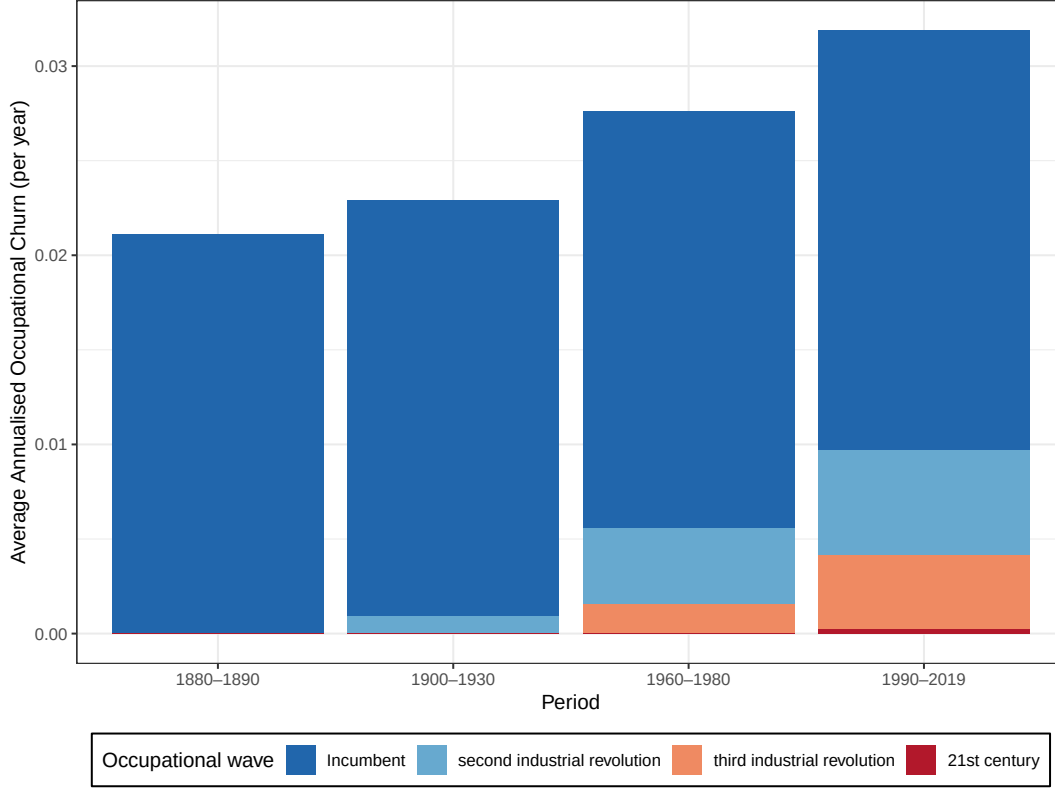
To this end, we expand on Deming et al. (2025) and use occupational “churn” to investigate changes to the occupational structure over time, and the dynamism associated with each period. Deming et al. (2025) define *churn* for an occupational group as the absolute value of the difference in employment shares between two periods. Churn in the entire economy are the sums of these absolute differences. If churn is close to 0, there is little turnover in the economy. We compute *churn* for each year using HISCO-codes and then consider the average yearly churn across our 30-year periods.

$$\text{Churn}_p = \frac{1}{N_p} \sum_{t \in T_p} \sum_h \frac{|s_{h,t} - s_{h,t-1}|}{g_t} \quad (1)$$

where T_p is the set of observation years falling within period p , $N_p = |T_p|$ is the number of such observation years, $s_{h,t}$ denotes HISCO h ’s share of total employment in year t (with $t - 1$ the previous observation year), and g_t is the number of calendar years between observations t and $t - 1$, so that churn is expressed per year regardless of the spacing of censuses. The 1960 and 2001 cross-scheme transitions are included in the baseline; Figure A1 recomputes period churn excluding them.¹⁶

¹⁶Churn as defined here captures reallocation among continuing occupations: an occupation’s first appearance and its eventual exit contribute no share change, since $|s_{h,t} - s_{h,t-1}|$ is computed only between consecutive observations of the same occupation. Periods in which many occupations enter or exit therefore

Figure 7: Occupational Churn 1880-2019



Note: Average annualized occupational churn by 30-year period, computed at the 5-digit HISCO level per Equation 1. *Source:* IPUMS 1880–1910; Swedish 1930 census (50% sample); FOB 1960–1990; LISA 2001–2019.

Figure 7 documents that churn systematically increases over time. Churn has never been more potent than during our last period, stretching from 1990 until 2019, and the rise accelerates markedly in this final interval. Interestingly however, despite the recurrence of new technological waves, almost all of the turnover occurs within the incumbent pool. Just as incumbent occupations dominate the levels of employment, they dominate its dynamics. We highlight this in Figure 8 where we compare employment shares by wave to the contribution to churn.

Let $\mathcal{H}_w$ denote the set of HISCO codes belonging to wave $w \in \mathcal{W}$. Because the summand in Equation 1 is additive across occupations, period churn decomposes exactly into wave contributions:

$$\text{Churn}_{w,p} = \frac{1}{N_p} \sum_{t \in T_p} \sum_{h \in \mathcal{H}_w} \frac{|s_{h,t} - s_{h,t-1}|}{g_t}, \quad \sum_{w \in \mathcal{W}} \text{Churn}_{w,p} = \text{Churn}_p. \quad (2)$$

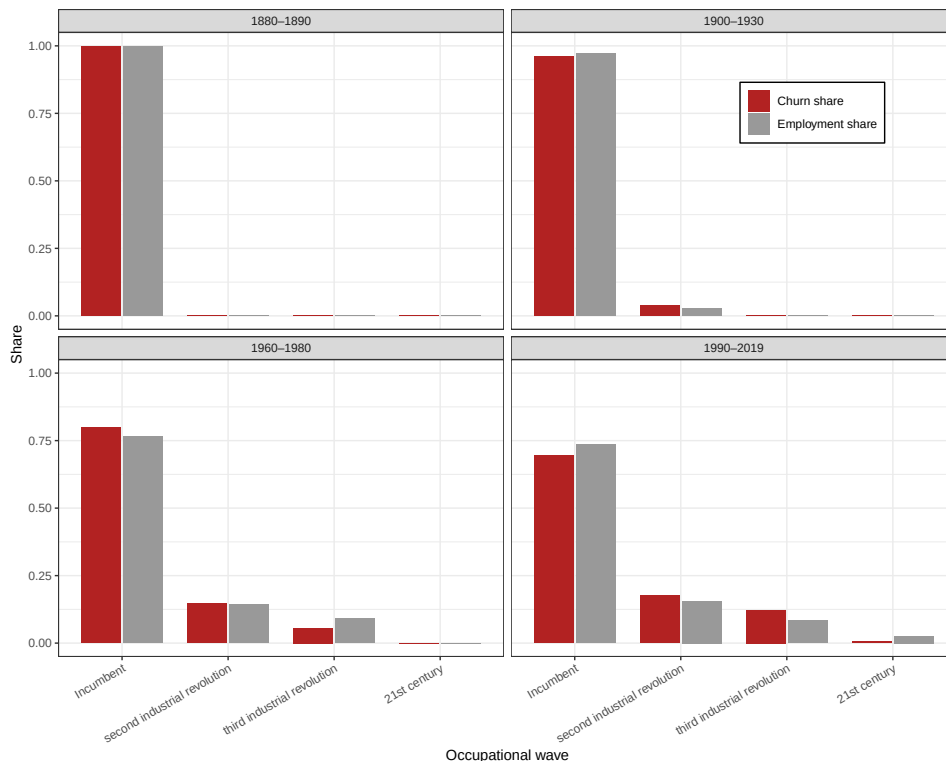
Figure 8 compares each wave’s share of the period’s churn with its share of employment over the same years,

$$\chi_{w,p} = \frac{\text{Churn}_{w,p}}{\sum_{w' \in \mathcal{W}} \text{Churn}_{w',p}}, \quad e_{w,p} = \frac{\sum_{t \in T_p} \sum_{h \in \mathcal{H}_w} E_{h,t}}{\sum_{t \in T_p} \sum_h E_{h,t}}, \quad (3)$$

appear less, not more, dynamic by this measure. We additionally drop single-occupation share changes of 0.05 or more in all churn figures, which removes a handful of coding artefacts.

where $E_{h,t}$ is employment in HISCO h in year t . Both shares sum to one within a period. A wave with $\chi_{w,p} = e_{w,p}$ contributes to turnover exactly in proportion to its size; $\chi_{w,p} > e_{w,p}$ means it generates more churn than its headcount implies.

Figure 8: Occupational Wave Contribution to Churn vs Employment Share



Note: Each occupational wave's share of total employment compared with its share of total churn, by 30-year period. Churn is computed at the 5-digit HISCO level per Equation 1. A churn share above the employment share indicates that the wave over-contributes to reallocation relative to its size. *Source:* IPUMS 1880–1910; Swedish 1930 census (50% sample); FOB 1960–1990; LISA 2001–2019.

The incumbent occupations are proportional to the employment shares. What is striking instead, is the oversized contribution of the second industrial revolution, and the undersized contribution of the third industrial revolution jobs. New jobs from 1960 onward thereby contribute little to this increase in labor market dynamics, not just because of their smaller employment shares, but also because of their relatively smaller proportional churn. This observation reconciles our two earlier findings. That most people work in incumbent occupations and that the labor market is highly dynamic are not competing stories but the same one: the persistent incumbent pool is also the most reshuffled. Structural change operated largely through the reallocation of labor within the existing set of occupations rather than through the entry of entirely new ones.¹⁷

¹⁷Because churn might be artificially high when the underlying occupational classification changes, Figure A1 recomputes period churn excluding the 1960 and 2001 cross-scheme transitions.

3.3 Occupational survival

To analyze which occupations that survive in the long run, we shift the unit of analysis from employment shares to the individual occupation. Concretely, we use a regression framework and consider the impact of occupational characteristics, such as the Smithian and the Schumpeterian scores and the technological wave, on the probability of an occupation surviving, defined as an occupation employing more than 50 people.¹⁸ We use a Cox proportional hazard model to estimate the impact of an occupation’s schumpeterian and smithian score on its survival, as well as which wave an occupation belongs to.

$$h_i(t) = h_0(t) \exp \left(\beta_S \text{Schump}_i + \beta_M \text{Smith}_i + \sum_{w \in \mathcal{W}} \gamma_w \mathbf{1}\{\text{Wave}_i = w\} \right) \quad (4)$$

Table 2 reports the estimates from Equation 4. While the point estimates are positive, we find no significant effect for schumpeterian scores. Instead, we find substantial effects from being more smithian. Occupations that are smithian are more likely to survive. Increasing the smithian score by one decreases the hazard of falling below the threshold by roughly 40%.

When considering the survival across waves we show that newer occupations are more likely to disappear compared to occupations that existed in the 1800s. Jobs that are new since 1960 are much less likely to survive than incumbent occupations. By contrast, occupations from 1900-1930 are considerably more likely to survive than these newer occupations, albeit still less likely to survive than incumbent occupations. Part of this is mechanical, jobs from the early 1900s are generally older throughout our dataset. However, the 1960-1990 jobs, have a similar age advantage compared to the 21st century jobs but experience no survival advantage.

4 Smithian vs. Schumpeterian Jobs

To consider the relative importance of Smithian/Schumpeterian jobs we utilize the division of each occupation into one of four quadrants, as visualized in Figure 2. The quadrants reflect the position above or below the median in either score.¹⁹ We then calculate the employment share of each quadrant over time. Figure 9 reports the findings of this exercise. Occupations with both low Schumpeterian and low Smithian scores see a significant decline, primarily driven by falling employment in the agricultural sector. Instead, jobs that are both highly technological and Smithian increase their relative share alongside jobs that are primarily division of labor driven. Only a small portion (less than ten percent) of employment is today in jobs that are above median technological but only to a small degree associated with a strong division of labor.²⁰

Although twenty-first-century occupations are, on average, the most Schumpeterian, this recent occupational wave is still dominated by jobs that also reflect Smithian processes. This is consistent with the mechanism described by Becker and Murphy (1992): new technologies and new knowledge do not only create

¹⁸In Figure A5 we allow this threshold to vary, producing similar results.

¹⁹We use global medians, computed by taking the median across all years.

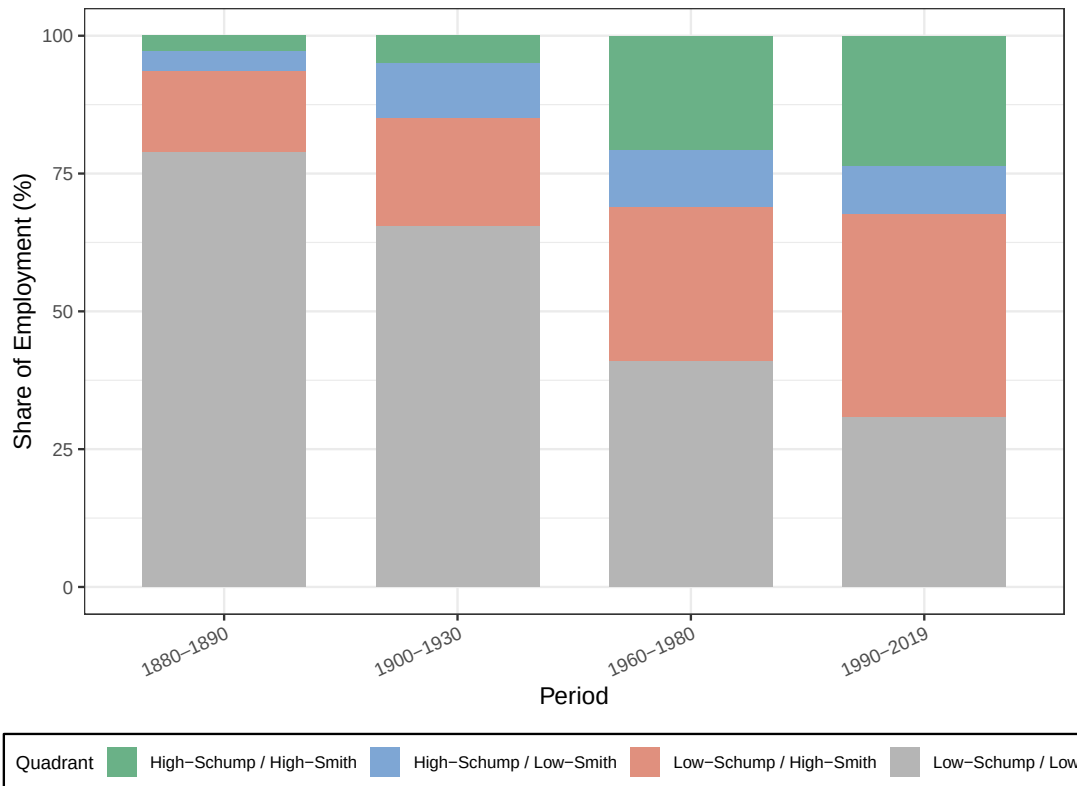
²⁰In 2019 the largest occupations in this quadrant were occupations such as automobile mechanics and tram drivers. Occupations which are associated with a distinct technology but that do not rely on a large and complex economy. In Figure A2 we further show that the average Schumpeterian score in occupations does not increase, for most occupational waves the Schumpeterian score is essentially constant, with the exception of third-industrial revolution jobs. However, the average Smithian score tends to increase and diverge from the Schumpeterian average. This reflects the pattern we see in Figure 9.

Table 2: Occupational Survival

	(1)	(2)	(3)
Schumpeterian score	1.200*	1.126	0.938
	[1.015, 1.419]	[0.959, 1.322]	[0.773, 1.138]
Smithian score	0.573***	0.532***	0.557***
	[0.488, 0.672]	[0.454, 0.625]	[0.461, 0.673]
Wave: 2nd ind. rev. (vs Incumbent)		1.454***	1.543***
		[1.148, 1.841]	[1.214, 1.961]
Wave: 3rd ind. rev. (vs Incumbent)		3.876***	3.928***
		[2.144, 7.008]	[2.159, 7.149]
Wave: 21st century (vs Incumbent)		2.551**	2.566**
		[1.147, 5.674]	[1.107, 5.949]
Num.Obs.	549	549	549
Major group (1-digit HISCO) strata	No	No	Yes

Note: *Cox proportional-hazards ladder. Hazard ratios ($\exp\beta$) with HISCO-clustered 95% confidence intervals in brackets. Significance: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. $HR > 1$ = higher death hazard vs the Incumbent reference wave. Calendar year is the baseline-hazard axis throughout. Death threshold = 50 workers; 325 deaths across 549 occupations. Source: IPUMS 1880–1910; Swedish 1930 census; FOB 1960–1990; LISA 2001–2019.*

Figure 9: Share of Employment by Quadrant



Note: Share of total employment in each Smithian/Schumpeterian quadrant by 30-year period. Quadrants are defined by whether a HISCO's time-averaged scores fall above or below the cross-occupation medians (Smithian = 2.33, Schumpeterian = 2.00), computed globally across HISCOs and years. *Source:* IPUMS 1880-1910; Swedish 1930 census (50% sample); FOB 1960-1990; LISA 2001-2019.

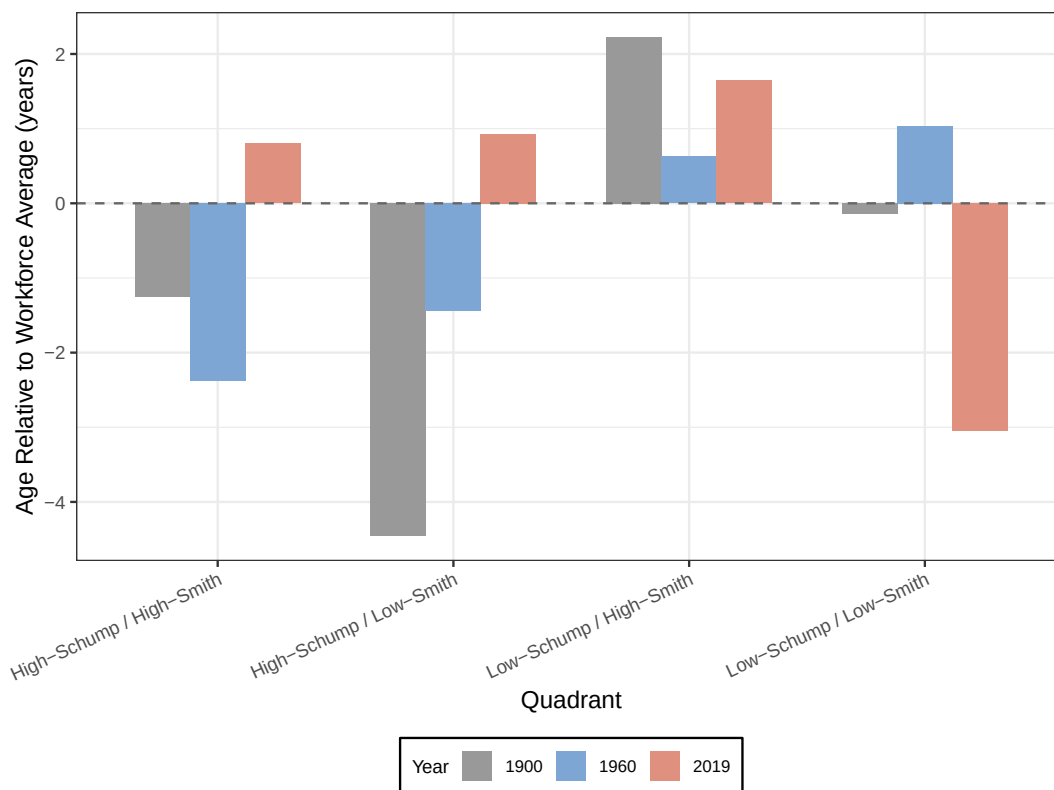
new economic functions, but also increase the returns to specialization within existing ones. As a result, the modern occupational structure has become increasingly shaped by jobs made possible by a finer division of labor, even when those jobs originate in periods of rapid technological change.

4.1 Which jobs are getting old?

In this section we consider the demographic composition of workers in different categories. We are, in particular, interested in two questions, how the gender structure and how the relative age of workers within an occupation has changed. Following Autor and Dorn (2009), we begin by tracing the relative age of workers in different occupations, doing this as a way of capturing whether an occupation was in decline or not. When an occupation is new the relative age of employed workers in the occupation should be young, whereas an occupation that is in decline should see an increasingly older workforce. Furthermore, we consider that occupations driving technical innovation and structural change should feature a mostly young workforce.

To this end, we track the age structure within occupations to understand how this has changed over time. We consider the four quadrants of occupations, based on their Schumpeterian and Smithian scores, and then track the average worker age in each of these relative to the overall workforce average. Figure 10 reports results for 1900, 1960, and 2019.

Figure 10: Worker Age Relative to Workforce Average by Quadrant, 1900–2019



Note: Employment-weighted mean worker age within each Smithian/Schumpeterian quadrant, demeaned by the year-specific workforce average. Positive values indicate older than the workforce that year; negative values indicate younger. 1990 is excluded because age is not in the 1990 FOB. *Source:* IPUMS 1900; FOB 1960; LISA 2019.

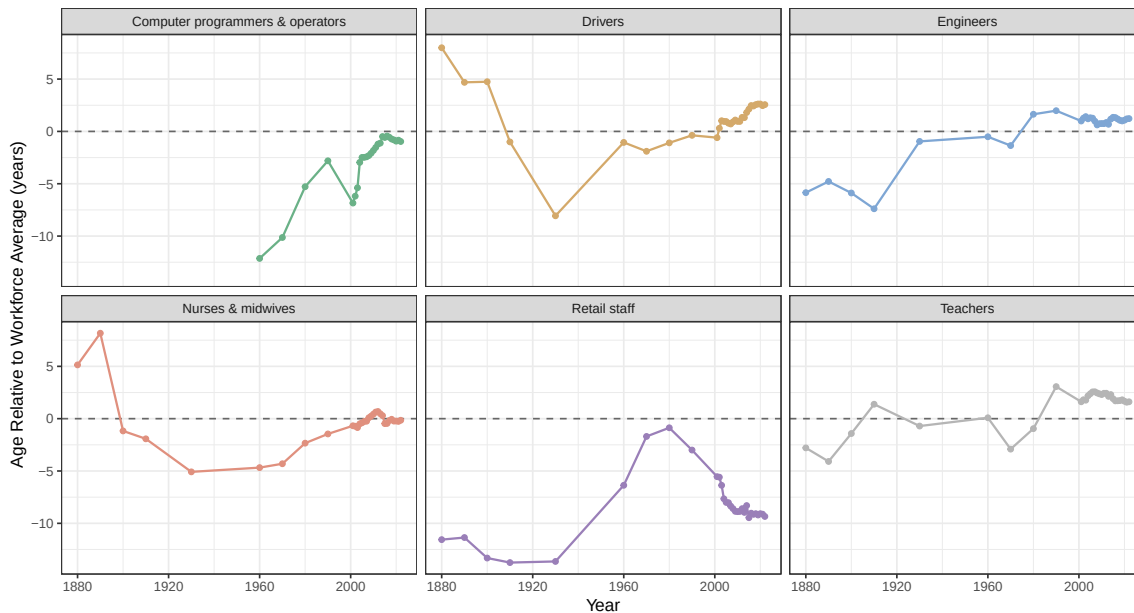
In the early twentieth century, both high-Schumpeterian quadrants had workforces that were distinctly younger than the overall average. High-Schumpeterian, low-Smithian occupations—jobs tied to technology but not embedded in a deep division of labor, such as automobile mechanics and tram drivers—were especially young. By 1960, the high-Schumpeterian, high-Smithian quadrant remained the youngest, consistent with a period in which technology-intensive occupations were still expanding and attracting new entrants.

By 2019, this pattern has reversed. Both high-Schumpeterian quadrants now have workforces that are older than the workforce average. This shift is consistent with the regression results in Section 3.3: technology-driven occupations face higher risk of significant decline, and as they mature, they cease to attract young workers at the same rate. Conversely, the low-Schumpeterian, low-Smithian quadrant—which includes occupations such as auxiliary nurses, general laborers, and retail workers—has seen a striking shift in the opposite direction, going from a workforce near the average age to one that is substantially younger than average by 2019.

To illustrate this dynamic at the occupational level, we consider a set of occupations related to technology: Engineers which are archetypically Schumpeterian; Computer programmers & operators; drivers who are distinctly tied to technology. We also consider a set of less schumpeterian occupations: retail staff; nurses & midwives; and teachers. Figure 11 show the relative age trajectories for these occupations. For teachers, the

pattern is mostly stable, hovering around the workforce average. Engineers have been similarly stable since at least 1930. More concerning however, is the long-run pattern for computer programmers and operators. In the 1960s and 70s, these workers were on average at least 10 years younger than the rest of the workforce. Today, however, these workers are more or less average, a significant aging of this workforce. Retail staff exemplifies the aggregated age shift from Figure 10, moving in opposite to the more technological occupations with a significant drop in the relative age.

Figure 11: Relative Age of Selected Occupation Groups, 1880–2022



Note: Employment-weighted mean worker age in six HISCO occupation groups, demeaned by the year-specific workforce average (positive values indicate older than the average worker that year). Groups: engineers (43 codes, 02000–02990 and 03020–03990), computer programmers and operators (08420, 34220), nurses and midwives (071xx–073xx), teachers (13xxx), drivers (985xx), and retail staff (451xx). Points before 2001 are census/FOB benchmarks; from 2001 the series is yearly register data. Yearly observations keep only occupation codes measured in the current or preceding year, excluding stale codes carried forward in the register. Demeaning is done within source. *Source:* IPUMS 1880–1910; Swedish 1930 census (50% sample); FOB 1960–1990; LISA 2001–2022.

A concern might be that changes to the age structure is driven by changes to the educational system. If computer programmers, engineers or nurses require more education today compared to 1960 the entry into these jobs will be delayed and ages increase. To cope with this we run a test where we regress age on binary variables indicating occupational group, we interact this with a year dummy to gauge changes over time and run two specifications with and without an educational control. Figure A6 displays the results of this, showing that holding education constant does not move the point estimates in any way.

4.2 Which jobs are gendered?

While the age structure of the quadrants has shifted markedly over time, their gender structure is remarkably stable. Figure 12 shows the female share of employment in each quadrant relative to the workforce average in 1900, 1960, and 2019. Women are underrepresented in high-Schumpeterian, high-Smithian occupations by

roughly 16 percentage points in all three benchmark years—a gap that has persisted essentially unchanged across three technological waves, even as the female share of the workforce as a whole rose dramatically.²¹ The high-Schumpeterian, low-Smithian quadrant has instead masculinized further, as it came to be dominated by blue-collar, machine-related occupations such as drivers and mechanics. Women are instead overrepresented in the low-Schumpeterian, high-Smithian quadrant—specialized occupations in care, education, and administration. The Schumpeterian segment of the labor market has, in other words, remained male territory throughout our entire period, while the growth of female employment has been absorbed almost entirely by Smithian specialization within low-technology functions.

A tempting reading is that something inherent in technology-intensive work explains the persistent male dominance of the Schumpeterian quadrants. The historical record speaks against such a simple interpretation. Research on gender and technology has shown that the gender coding of technical work is the outcome of struggles over who controls new tools and the knowledge required to operate them (Cockburn, 1983; Wajcman, 2010), and that the gender label of a job is typically assigned at the moment the job is created and thereafter naturalized as an inherent feature of the work (Milkman, 1987). Episodes of technological change are therefore critical junctures: when a new technology reorganizes production, the gender of the associated work is renegotiated, and men, controlling technical education and professional institutions, have typically won that renegotiation. Sommestad (1994) provides a classic Swedish illustration: skilled dairy work, for centuries a female craft, was recoded as masculine when industrialization brought the cream separator and science-based dairy education, not because the new technology demanded male labor but because men monopolized the machinery and the formal training that came with it.²²

Computer programming, the archetypal Schumpeterian occupation of the third industrial revolution, followed the same pattern. Programming initially emerged as feminized, quasi-clerical labor: the first programmers of the American ENIAC were women, recruited from the ranks of female “computers” who had performed calculation work by hand (Light, 1999). Over the 1960s and 1970s, as the economic and professional stakes of the occupation became apparent, programming was systematically recoded as masculine: aptitude tests and personality profiles modeled on the existing male workforce, professionalization campaigns, and the construction of a distinctively masculine expert culture together transformed a routine, feminized activity into well-paid men’s work (Abbate, 2012; Ensmenger, 2010, 2015; Hicks, 2017). By the time programming entered our high-Schumpeterian, high-Smithian quadrant as mass employment, its gender code had hardened into the apparent natural order that Figure 12 records.

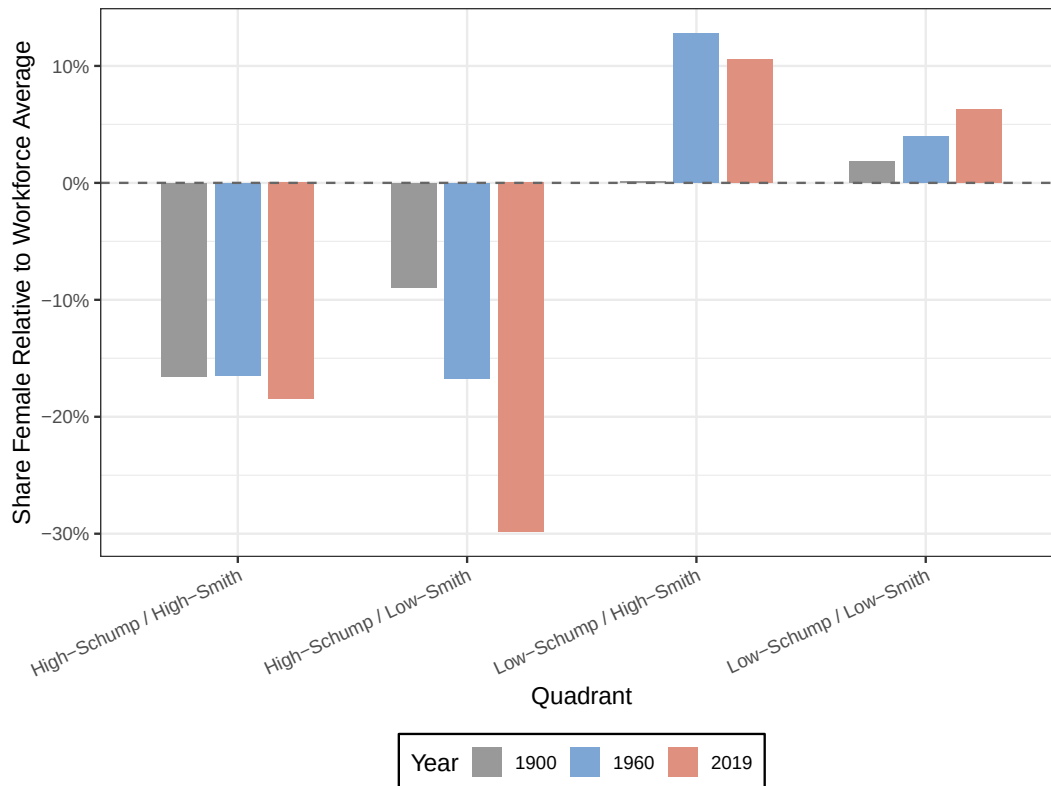
This mechanism also explains why the renegotiation so consistently favors men. In the queueing framework of Reskin and Roos (1990), workers at the front of the labor queue, historically men, claim new occupations with high rewards, while Goldin (2014) shows that men resist female entry precisely in young occupations whose status is still being established.²³ Both mechanisms help explain the persistent male dominance of the Schumpeterian quadrants. Importantly, however, this segregation does not in itself translate into lower earnings for women: as we show in Section 4.3, it is the degree of specialization rather

²¹The absolute female share has increased in all four quadrants, as shown in Figure A4; the increase in the high-Schumpeterian, low-Smithian quadrant has, however, been minimal.

²²Swedish research has documented the same dynamic in industrial work and engineering (Berner, 1996; Wikander, 1988). The process could also run in the opposite direction: Florin (1987) shows that elementary-school teaching feminized as the state expanded schooling on the cheap and men moved to better-paid alternatives.

²³Feminization, when it occurs, is also consequential for pay: occupations that feminize lose relative wages (Levanon et al., 2009), and male flight from feminizing occupations exhibits tipping dynamics (Pan, 2015).

Figure 12: Female Share Relative to Workforce Average by Quadrant 1900–2019



Note: Employment-weighted share female within each Smithian/Schumpeterian quadrant, demeaned by the year-specific workforce share female. Positive values indicate women overrepresented relative to the workforce that year; negative values indicate underrepresented. See Figure A4 for absolute (non-demeaned) levels. *Source:* IPUMS 1900; FOB 1960; LISA 2019.

than the technological content of an occupation that commands the largest wage premia, and women are overrepresented precisely in the highly specialized low-Schumpeterian quadrant. The gendered division of the labor market thus runs along the technological dimension rather than the earnings dimension. If the gender codes assigned at occupational birth are as durable as Figure 12 suggests, each technological wave reproduces, rather than erodes, men's hold over technical work, even as women's concentration in Smithian specialization places them in occupations with comparable returns.

The persistence of gendered sorting matters beyond its distributional consequences. From a macroeconomic perspective, if the aptitude for technical work is distributed equally across the sexes, the barriers documented above imply a misallocation of talent: Hsieh et al. (2019) estimate that the improved allocation of women and minorities across occupations accounts for a substantial share of U.S. productivity growth since 1960. Gender segregation may also impede the diffusion of knowledge, a central ingredient of long-run growth (Mokyr, 1990); Scarborough (2020) shows, in the U.S. context, that gender segregation slows growth precisely in industries that depend on such knowledge transfers. To the extent that the Schumpeterian segment of the labor market is small but catalytic, its continued closure to half the workforce is therefore a first-order concern.

4.3 Which jobs pay off?

In this section we consider whether schumpeterian jobs are associated with a wage premium. We also consider if there is a premium for new jobs, and how this has changed over time. Information on income is available to us earliest in the 1930 census and then for all our benchmark years from 1970 onward. Our point of departure is a simple earnings function that we expand to include local, occupational and educational controls, as well as our indicators for cohort/quadrant:

$$\log(\text{Income}_i) = \alpha_o + \beta \text{Quadrant} + \text{Age}_i + \text{Age}_i^2 + \text{Gender}_i + \text{Education}_i + \lambda + \theta + \epsilon_i \quad (5)$$

$$\log(\text{Income}_i) = \alpha_o + \beta \text{Wave} + \text{Age}_i + \text{Age}_i^2 + \text{Gender}_i + \text{Education}_i + \lambda + \theta + \epsilon_i \quad (6)$$

Where λ are a set of dummies for the three-digit hisco, and θ are a set of parish/municipality dummies.²⁴ We also control for the level of education to deal with individuals sorting into occupations by education. The findings are reported in Figure 13. Panel 13a shows earnings over for cohorts of occupations over time relative to jobs from the 1800s. Jobs from the second industrial revolution consistently pay the same as incumbent jobs from the 1800s. By contrast, jobs that were new between 1960 and 1990 see a large premium. Today, these occupations are, on average, the highest paying. Jobs from the 21st century pay similar to incumbent jobs. If anything, workers in these jobs earn slightly less than jobs from the 1800s.

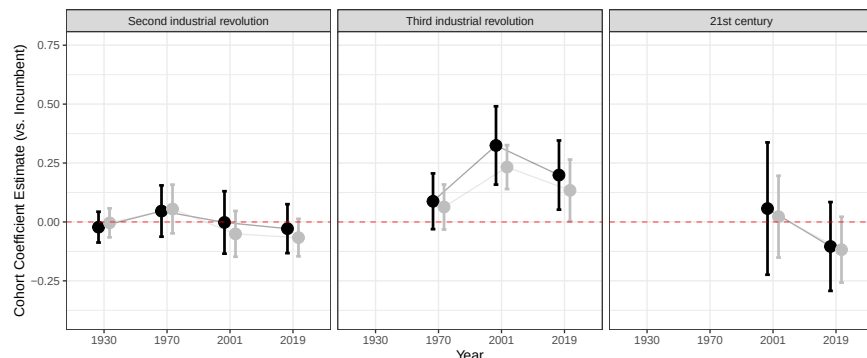
In Panel 13b, we show that jobs that are the most technologically advanced, and complex earn the most, occupations that are in the high-schump/high-smith quadrant, earn in excess of 25% more than someone in a low-low occupation. By contrast, jobs that are high-schump/low-smith have seen their earnings advantage move in a U-shape, falling from the 1930s, to being negative and today, earning slightly more than the low-low category. After accounting for differences in education among workers, jobs that are high-smithian but low-schumpeterian see similar earnings to the high-high-category. To account for general changes to the wage distribution we run the same models but use income rank as the outcome, showing that our general pattern is unlikely to be driven by an overall wage compression.²⁵

²⁴For the 1930 analysis we use parishes, from 1970 onward we use municipalities.

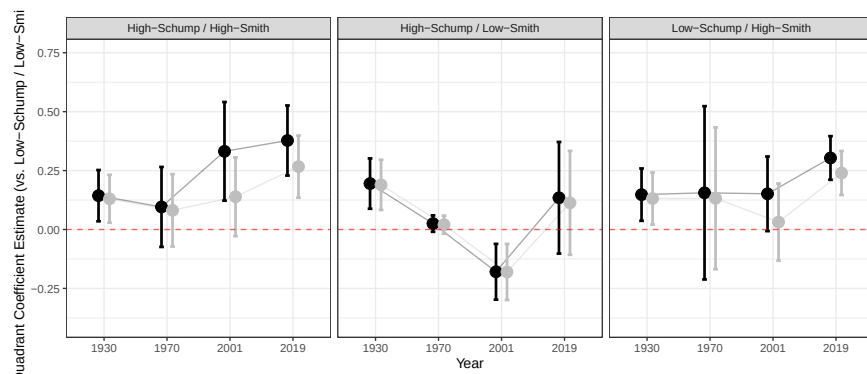
²⁵See Figure A7.

Figure 13: Income returns to occupational cohort and Schumpeter/Smith quadrant, 1930–2019.

(a) Cohort coefficients (vs. Incumbent).



(b) Quadrant coefficients (vs. Low-Schump / Low-Smith).



Note: Coefficients from log-income regressions with controls for age, age², and gender; the + *Education* series adds education. 95% CIs as vertical bars; SEs clustered at the HISCO level. *Source:* Swedish 1930 census (50% sample); FOB 1970; LISA 2001 and 2019.

5 Discussion

This paper has examined the long-run relationship between technological change and employment by studying the evolution of occupations in Sweden from 1880 to 2019. Using harmonized occupational data, we have asked not only whether new occupations appear, but how employment is distributed across old and new occupational functions. Our results point to a central conclusion: technological change has repeatedly transformed work, but it has not repeatedly remade the occupational structure from scratch.

Our main finding is that the occupational structure is considerably more persistent than accounts centered on technological disruption alone would suggest. Most workers today remain employed in occupations whose core economic functions were already present in the late nineteenth century. Although their tasks have been transformed by successive technological waves, the function of many jobs -care, teaching, transport, trade, administration, construction, repair, and coordination- have remained remarkably durable.

This persistence does not support a simple view in which technology repeatedly replaces old work with entirely new work. Rather, technological change has typically operated through a broader process of economic growth. New technologies raise productivity, expand markets, and increase demand; this in turn permits

a finer division of labor and creates new specialized occupations. Automation without growth would be a concern, since task displacement would then not be offset by expanding demand or new specialization, but the historical record shows that technological also led to the transformation of existing occupations and the creation of new ones.

Secondly, contrary to Deming et al. (2025) we do not observe any slow-down in labor market dynamics.²⁶ At our level of detail, the labor market appears more dynamic with evidence of increasing churn. Yet this churn occurs largely within the existing occupational structure and especially among incumbent occupations. The same occupational pool that accounts for most employment also accounts for much of the observed reallocation. Long-run persistence and rising churn are therefore not contradictory. They describe a labor market in which old functions remain important, but in which employment is continuously reorganized within and between occupations.

The more concerning result, on the other hand, is that the technological sector itself appears to have become less dynamic. Although Schumpeterian occupations account for a modest share of total employment, their importance lies in their catalytic role. They introduce new technologies, enable productivity growth, and create the conditions for further specialization elsewhere in the economy. Yet the occupations associated with the technological wave of the twenty-first century have not generated employment growth comparable to earlier waves, especially the second industrial revolution. We also do not find that newness itself is rewarded in terms of earnings premia. Instead we find that the highest earnings are found in occupations that have a high degree of specialization—no matter the technological content. It is this feature of work, rather than the technological age of the occupation, that rewards the highest returns. The issue is therefore not whether workers are displaced by automation. The issue is whether new technologies are generating enough high-return forms of work.

The demographic patterns reinforce this concern. By 2019, high-Schumpeterian occupations were no longer younger than the workforce average. In several cases, technological occupations appear to have aged as they matured. Perhaps most concerning is the rapid aging of computer programmers, suggesting a constrained inflow of younger workers. At the same time, women remain underrepresented in these occupations relative to the workforce as a whole. The small sector that is most directly connected to technological change is therefore not only limited in employment size, but also increasingly old and persistently gendered.

Taken together, the results suggest that the central question is not whether technological change destroys jobs. The more important question is instead whether technological change continues to generate the kinds of occupations that historically linked innovation to specialization, high returns, and broader employment growth.

²⁶Figure A1 shows a slowdown from the late 1990s to the 2000s, but churn was still on par with the late nineteenth and early twentieth centuries.

6 AI Statement

Generative AI has been used to assist in producing code, reviewing data, and editing text. AI was also used as described above to label data.

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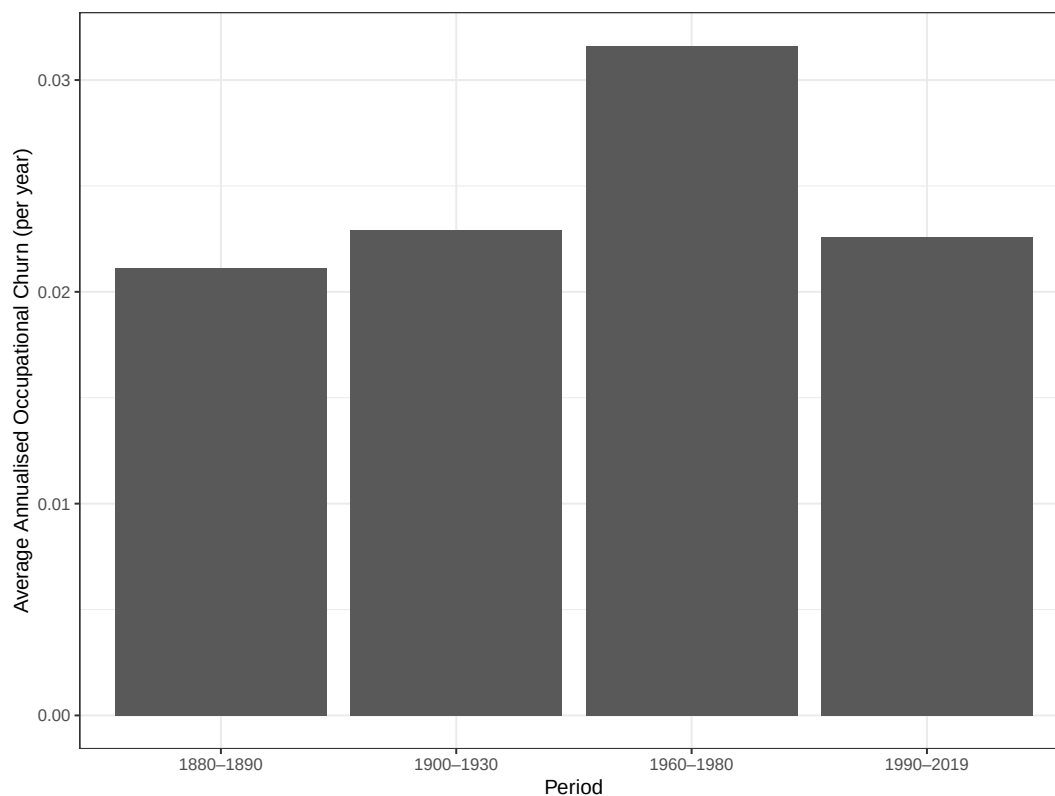
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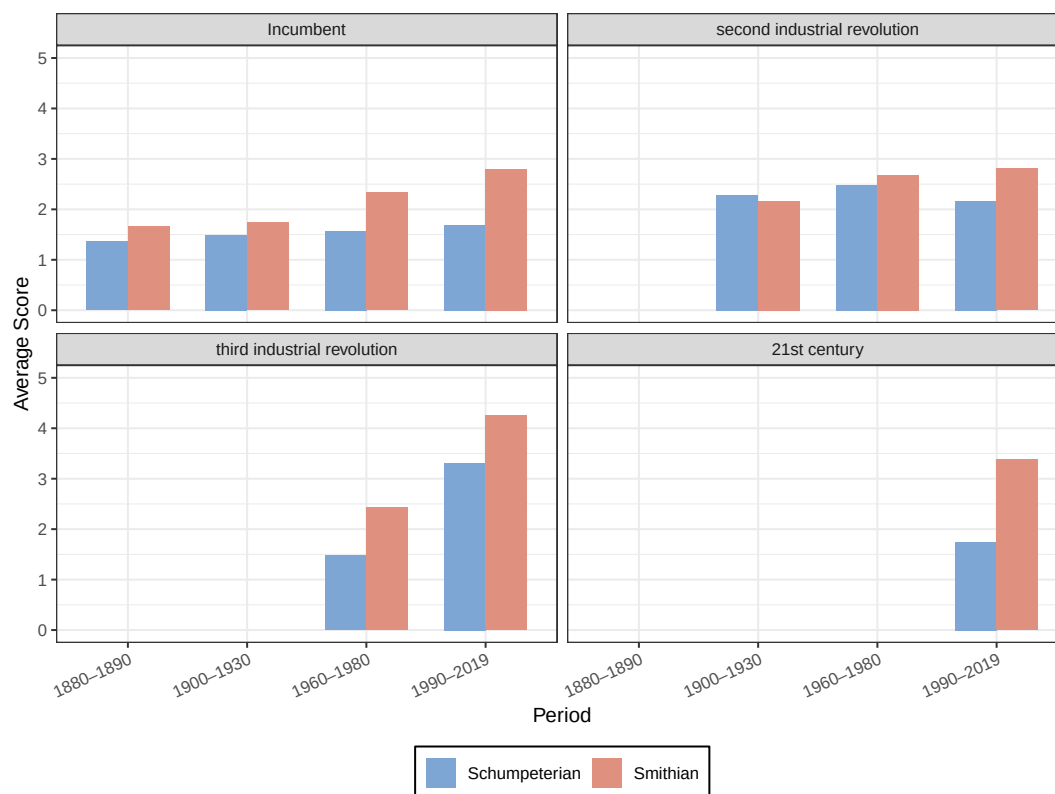
Figure A1: Occupational Churn Excluding Coding Breaks



Note: Average annualized occupational churn by 30-year period, computed at the 5-digit HISCO level per Equation 1, excluding the 1960 and 2001 coding-scheme transitions. The long-run increase in churn from Figure 7 is mostly unchanged. *Source:* IPUMS 1880–1910; Swedish 1930 census (50% sample); FOB 1960–1990; LISA 2001–2019.

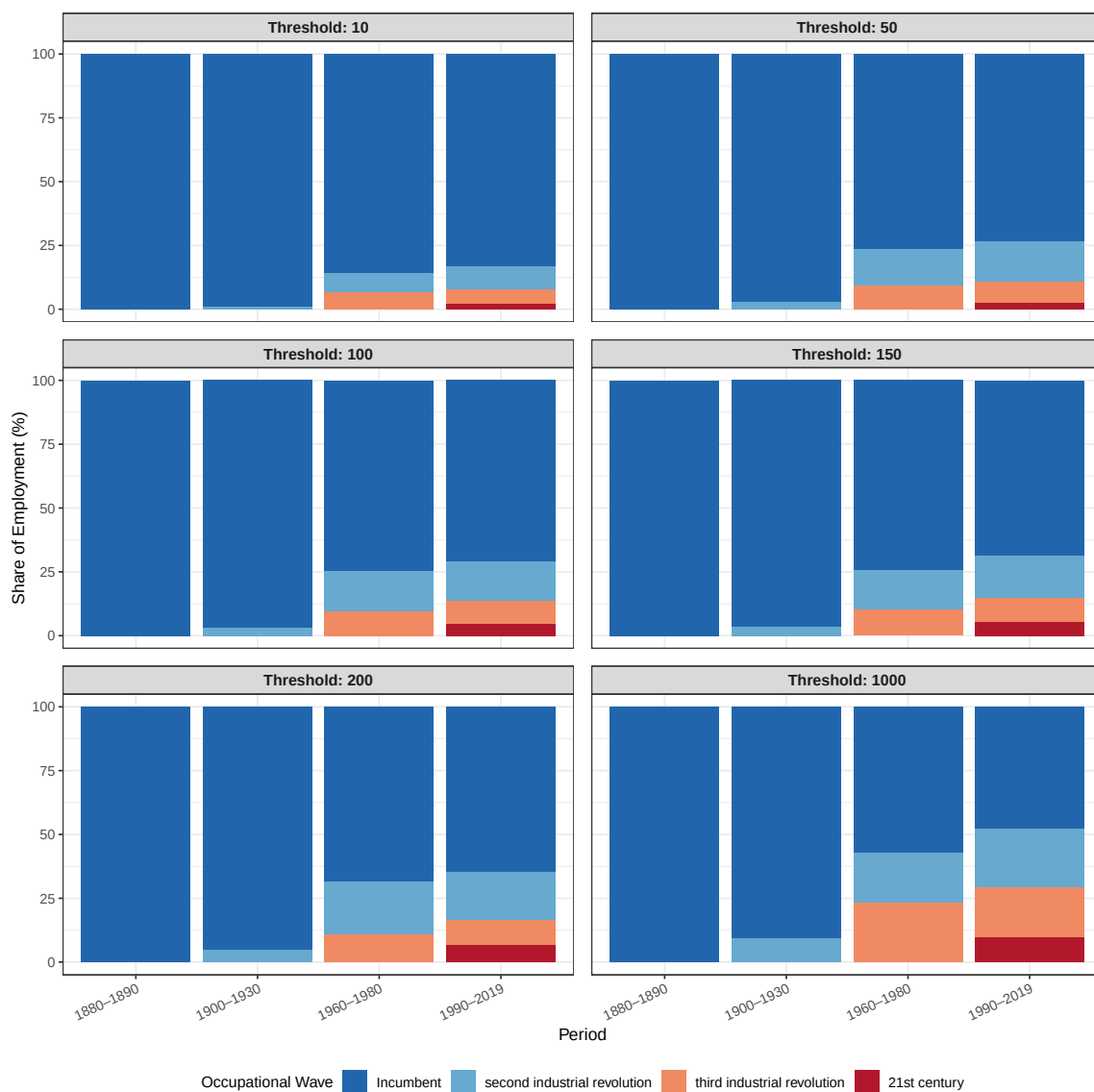
A Additional Tables and Figures

Figure A2: Average Smithian/Schumpeterian Job Score by Occupational Wave 1880-2019



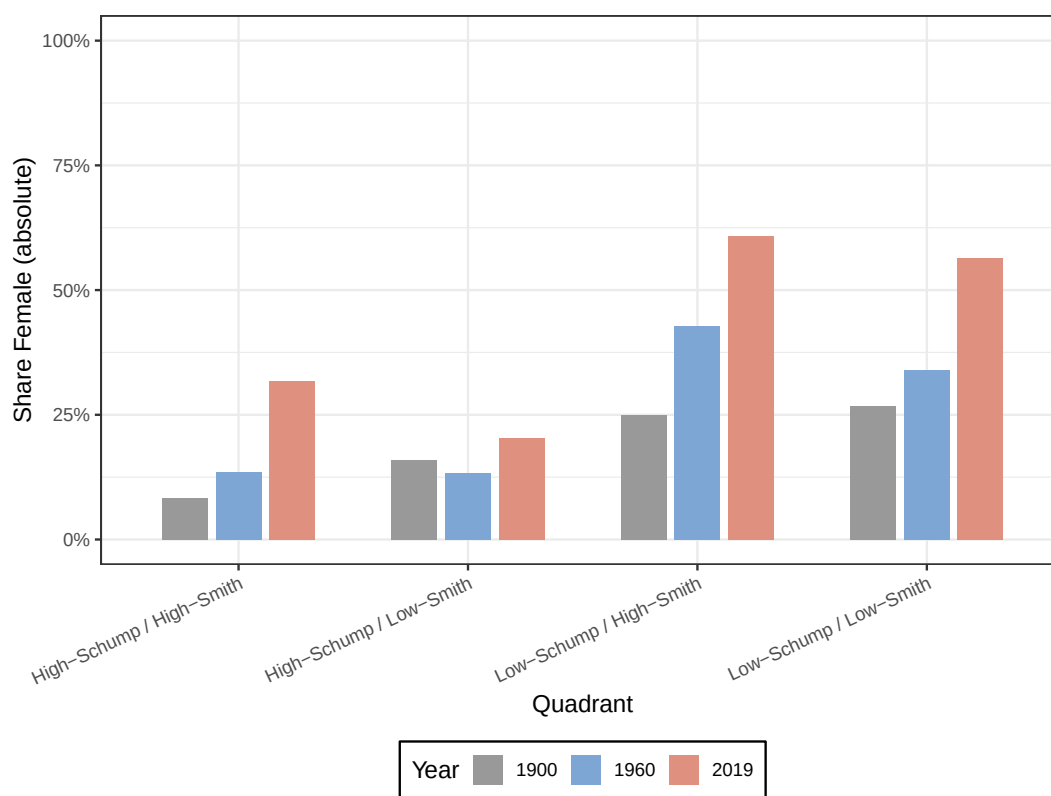
Note: Average Smithian (red) and Schumpeterian (blue) scores by occupational wave over time. Employment-weighted within each wave-year cell. *Source:* IPUMS 1880–1910; Swedish 1930 census (50% sample); FOB 1960–1990; LISA 2001–2019.

Figure A3: Employment Share by Wave 1880-2019 with Varying Thresholds



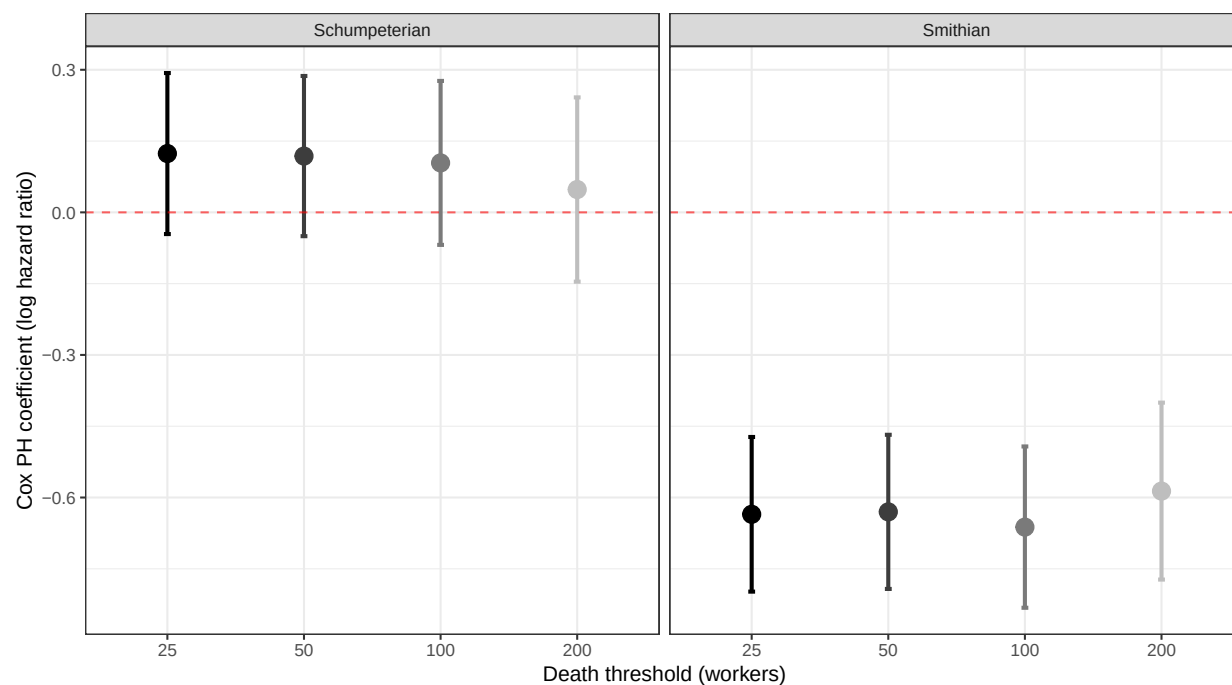
Note: Figure 6 replicated at alternative new-occupation thresholds (10, 50, 100, 150, 200, 1000). Wave composition is broadly stable across thresholds. *Source:* IPUMS 1880–1910; Swedish 1930 census (50% sample); FOB 1960–1990; LISA 2001–2019.

Figure A4: Female Share of Employment by Quadrant 1900-2019



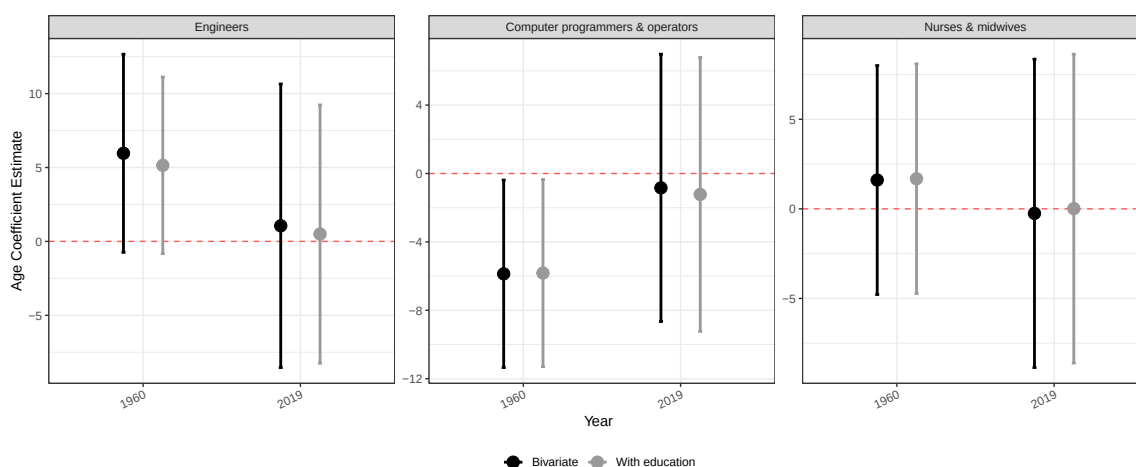
Note: Absolute (non-demeaned) employment-weighted share female in each Smithian/Schumpeterian quadrant. All four quadrants see substantial increases over time; the high-Schumpeterian / low-Smithian quadrant sees the smallest. *Source:* IPUMS 1900; FOB 1960; LISA 2019.

Figure A5: Occupational Characteristics vs Decline—Varying Thresholds



Note: Cox proportional hazards model from Table 2 re-estimated at alternative death thresholds (25, 50, 100, 200). Schumpeterian and Smithian coefficients shown; pattern stable across thresholds. 95% CIs; HISCO-clustered SEs. *Source:* IPUMS 1880–1910; Swedish 1930 census (50% sample); FOB 1960–1990; LISA 2001–2019.

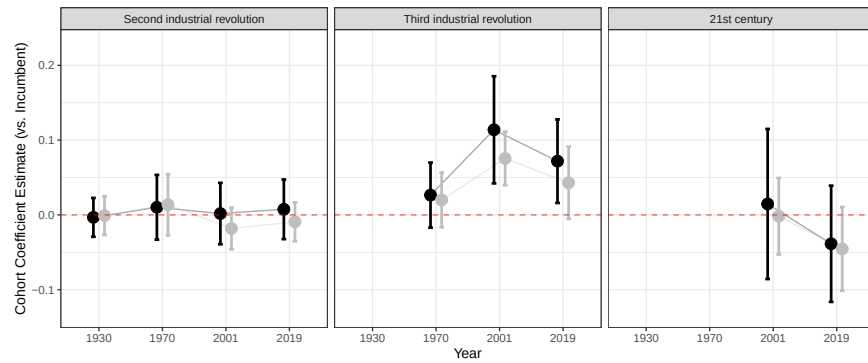
Figure A6: Age vs. Occupational Groups



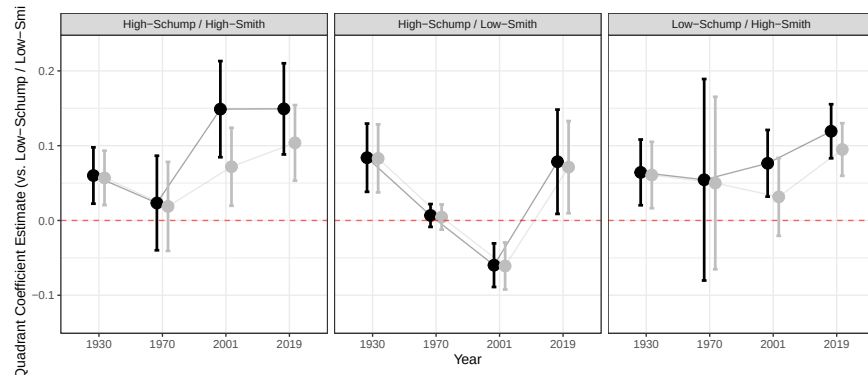
Note: Coefficients from regressions of individual age on occupation-group indicators interacted with year dummies, estimated with and without education controls. Each panel shows one occupational group; the two series per year are the bivariate specification and the specification adding education. 95% CIs as vertical bars; SEs clustered at the HISCO level. *Source:* Swedish registry data (FOB and LISA).

Figure A7: Ranked income returns to occupational cohort and Schumpeter/Smith quadrant, 1930–2019.

(a) Cohort coefficients (vs. Incumbent).



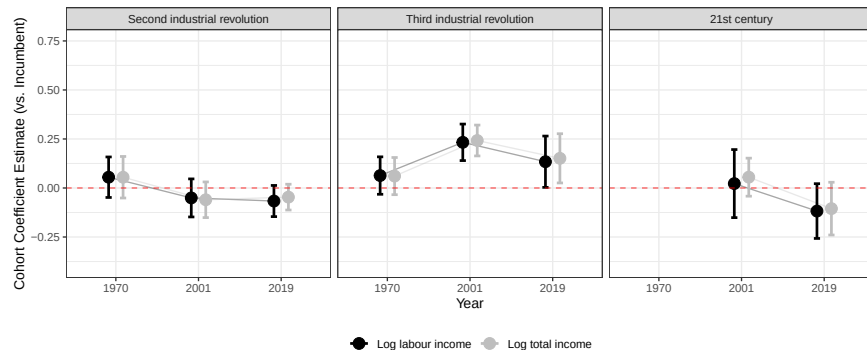
(b) Quadrant coefficients (vs. Low-Schump / Low-Smith).



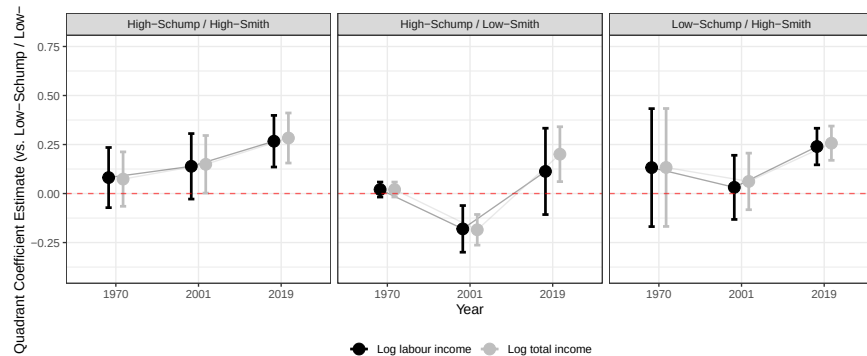
Note: Coefficients from ranked income regressions with controls for age, age², and gender; the *+ Education* series adds education. 95% CIs as vertical bars; SEs clustered at the HISCO level. *Source:* Swedish 1930 census (50% sample); FOB 1970; LISA 2001 and 2019.

Figure A8: Income returns to occupational cohort and Schumpeter/Smith quadrant, 1930–2019, total versus labor income.

(a) Cohort coefficients (vs. Incumbent).



(b) Quadrant coefficients (vs. Low-Schump / Low-Smith).



Note: Coefficients from income regressions with controls for age, age², gender and educational level. 95% CIs as vertical bars; SEs clustered at the HISCO level. Total income includes labor, capital, and income from business activity. *Source:* Swedish 1930 census (50% sample); FOB 1970; LISA 2001 and 2019.

B U.S. Codes and Comparison

Figure A9 provides a U.S. benchmark for our HISCO-based approach. We use microdata from the 1940 U.S. Census and the 2019 American Community Survey, both obtained from IPUMS (Ruggles et al., 2025). Since these data are not available in HISCO format, we harmonize U.S. occupational information to HISCO using OccCANINE (Dahl et al., 2024). For the 1940 Census, we use the original occstring variable, which contains occupational descriptions similar to those available in the Swedish censuses prior to 1960. For the 2019 ACS, we use the OCC variable, which provides occupational information more comparable to modern Swedish register data.

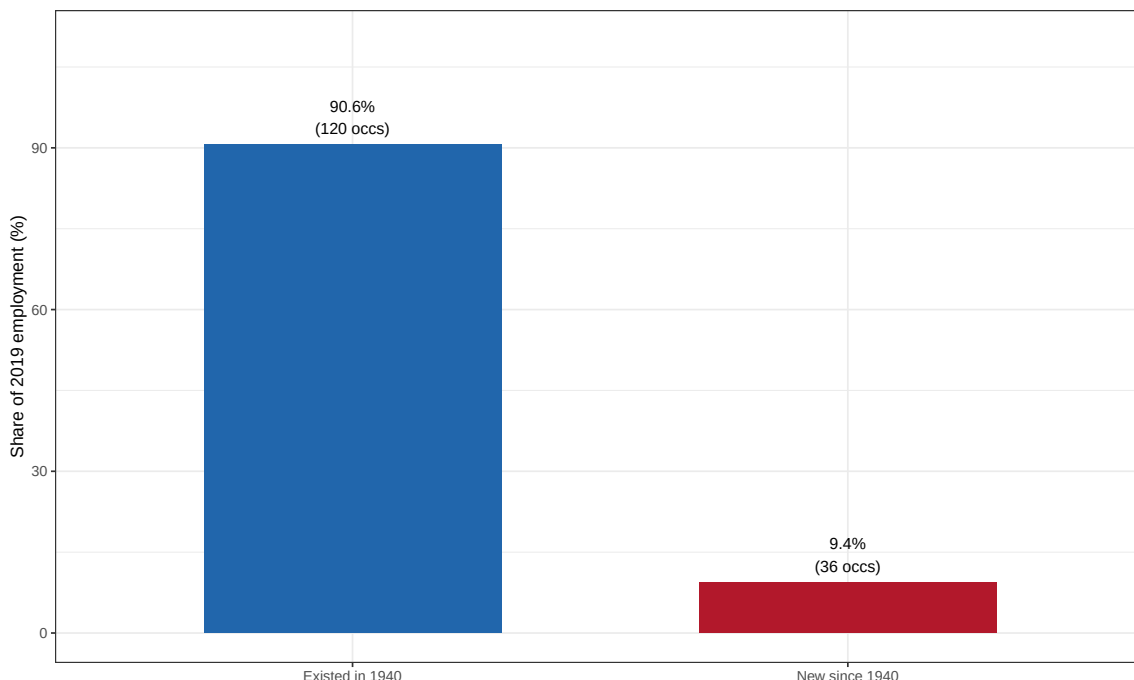
As in the Swedish analysis, we define an occupation as present in a given year if at least 1 in 25,000 workers are employed in it—the same relative threshold as the Swedish 50-worker cutoff, which corresponds to roughly 1 in 25,000 of the 1880 coded workforce. Applied to the PERWT-weighted 1940 counts this is approximately 1,850 weighted workers, or about 18 sampled persons in the 1 per cent sample, comfortably above sampling noise.²⁷ This allows us to classify HISCO occupations observed in 2019 according to whether

²⁷We review all the codes that are considered new and recode them as old if they are obvious false-positives.

they were already present in the U.S. occupational structure in 1940. We identify 36 occupations as new since 1940 out of the 156 HISCO codes observed in 2019. Figure A9 shows that these new occupations account for a minority of total U.S. employment in 2019, while a substantial share of employment remains in occupations already observed in 1940. The largest occupation in the 2019 U.S. data is salespersons, which alone accounts for 5.5 per cent of employment and is classified as an incumbent occupation under our HISCO-based measure.

This exercise differs from Autor et al. (2024), who identify new work from occupational titles entering existing and consistent Census occupation codes. Since employment in these underlying titles is not directly observed, their approach cannot directly track employment growth in the new titles themselves. By contrast, our HISCO-based approach follows consistent occupational groups over time and identifies when such occupations first appear in the data.

Figure A9: Occupational Persistence in the U.S. 1940-2019.



Note: Share of 2019 U.S. employment accounted for by occupations that existed in 1940 (Incumbent) versus those first appearing after 1940 (New). Occupation strings coded to HISCO via OccCANINE (Dahl et al., 2024); an occupation is treated as existing in 1940 if it had at least 1 in 25,000 PERWT-weighted workers (the same relative threshold as the Swedish 50-worker cutoff). PERWT-weighted throughout. *Source:* IPUMS 1940 1% sample; 2019 American Community Survey.

C Job Classifications

We classify jobs according to their technological relatedness and their degree of division of labor. Jobs can either be *Schumpeterian* or *Smithian*. Jobs that stem from technological innovation, are jobs that we deem to be *Schumpeterian*. Conversely, occupations that stem from an increased division of labor, and increased demand, are jobs that we view as *Smithian*. To classify occupations we utilize the Claude OPUS 4.5 model,

and a fewshot strategy—meaning we feed the LLM with a few examples of correct coding.²⁸

We use the following prompt:

I want you to code occupations according to their technological intensity. Go through each occupation listed in the excel file and do the coding task below. Save the results in a new excel file, one row for each occupation. Keep occupational code and occupational description. Coding task: Are jobs Smithian or Schumpeterian?

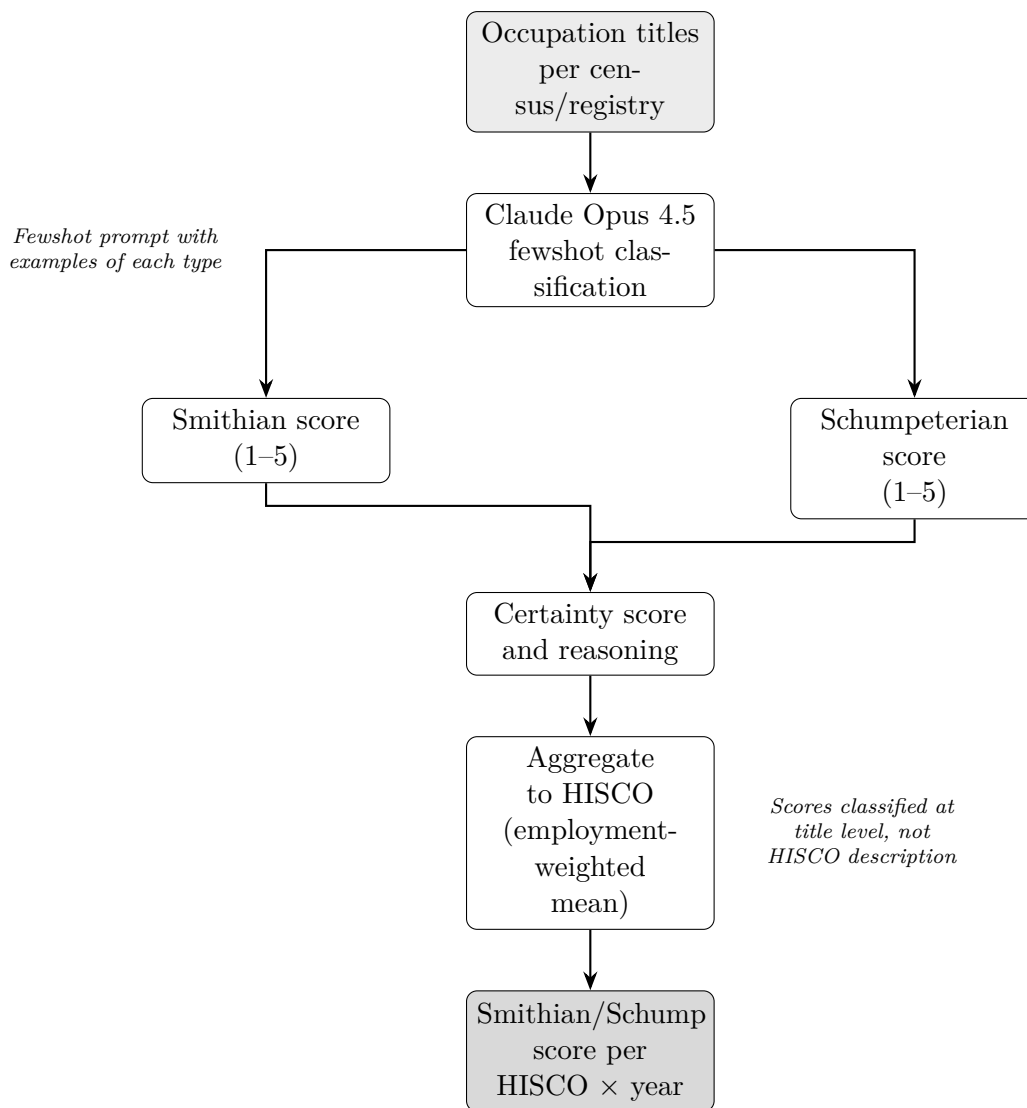
- *Smithian jobs are jobs such as economist, hr-specialist, nurses etc. (driven by demand and division of labor.*
- *Schumpeterian jobs are directly tied to technology, computer programmers, electricity workers etc.*

The occupational titles are found in the column: "column_name" Give a score from 1-5 for Smithian and for Schumpeterian respectively. Also give a certainty score from 0-1 for your assessment, and the reasoning.

Figure A10 summarizes the classification pipeline.

²⁸More specifically, we use the Claude OPUS 4.5-20251101.

Figure A10: Smithian/Schumpeterian Classification Pipeline



Note: LLM-based classification pipeline. Occupational descriptions are passed to Claude Opus 4.5 with a fewshot prompt; the model returns 1–5 Smithian and Schumpeterian scores plus a certainty score. Aggregated to HISCO by employment-weighted mean. *Source:* Authors’ illustration.

Note that we classify the underlying occupational titles/descriptions as schumpeterian/smithian, not the HISCO descriptions themselves. This approach has the benefit of allowing for changes within HISCO codes, noting that there might be new technological development within an occupation itself. We aggregate back to HISCO by calculating a mean schumpeterian/smithing score weighted by employment.

C.1 How Accurate are the Schumpeterian/Smithian Scores?

To check the relevance of our scores we compute the semantic similarity between occupational strings and bundles of technologically related words. We then compare these similarity scores to our Schumpeterian scores. If our schumpeterian scores are capturing technological relatedness, occupations with high Schumpeterian scores should also be more semantically related to our bundles of technology.

We begin by constructing a set of word bundles related to different technologies. Each bundle groups Swedish-language nouns associated with a distinct technological domain—electrification, mechanical/transport, communication, ICT, and science/R&D. Occupational titles (*ingenjör*, *forskare*, etc.) are deliberately excluded so that the resulting similarity score reflects proximity to *artefacts and concepts* rather than to occupation names that would tautologically match the SSYK descriptions. The five bundles are listed in Table 3.

Table 3: Swedish Word Bundles for the Schumpeterian Robustness Check

Bundle	Words
Electrification	electricity, electric current, electronics, battery, energy, steam, nuclear power, solar energy, power plant
Mechanical / Transport	machine, engine, truck, car, tractor, locomotive, aeroplane, ship, workshop, factory
Communication	telephone, telegraph, radio, television, satellite
ICT	computer, internet, software, hardware, programming, algorithm, code, robot, automation, semiconductor, microchip, processor, transistor, artificial intelligence
Science / R&D	technology, engineering, science, research, innovation, invention, patent, laboratory, experiment

Note: Five themed bundles of Swedish-language nouns, shown here in English translation; the embeddings use the Swedish originals. Each occupation description is compared with the L2-normalised centroid embedding of each bundle to obtain a per-bundle cosine similarity. Embeddings are produced by the KBLab *sentence-bert-swedish-cased* model. *Source:* Authors’ construction.

For each SSYK-2012 occupation in 2019 we embed the Swedish occupation description (*vardebenamning*) with the KBLab Swedish sentence-BERT model and compute the cosine similarity to each bundle’s centroid embedding. This yields five similarity scores per occupation—one per bundle—that can be compared with the Schumpeterian score. Table 4 reports the results in five panels. Panel A provides reference baselines: the overall employment-weighted mean similarity across all 429 occupations and the standard deviation across occupations. Panels B–E report *normalised* similarities: each raw similarity is divided by the corresponding bundle’s all-occupation employment-weighted mean (Panel A, first row), so a value of 1 means an occupation is exactly as similar to the bundle as the average occupation, and 1.10 means 10% more similar. Panel B aggregates occupations into the five integer Schumpeterian bins and reports the employment-weighted mean normalised similarity in each bin. Panels C, D and E zoom into the five largest 2019 occupations at the bottom (score = 1), middle (score = 3) and top (score = 5) of the Schumpeterian scale.

Occupations with high Schumpeterian scores tend to be more semantically similar to our technological bundles. These similarities are, however, not a general technological relatedness but a specific one. Occupations that score a five on our schumpeterian scale are weakly related to the communications bundle, but strongly related to the ICT and science bundles. The electrification bundle is most related to occupations scoring a four on our scale, and occupations that score a three also score highest on our mechanical bundle. The lowest schumpeterian scores are most related to the communications bundle. This appears to be driven by semantic similarities between individual occupations such as Care assistants. Overall, this exercise validates our Schumpeterian score, highlighting that this picks up on occupations containing words that are semantically similar to specific technologies.

Table 4: Normalised Per-Bundle Similarity Scores: Reference Baselines, Means by Schumpeterian Score, and Largest Occupations at the Bottom, Middle and Top of the Scale

SSYK	Occupation / Group	Employment	Schump.	Electrif.	Mech.	Comm.	ICT	Science
<i>Panel A. Reference baselines across all 429 occupations (raw similarities)</i>								
—	All occupations (employment-wt. mean)	5,195,211	—	0.297	0.396	0.342	0.352	0.370
—	Std. dev. across occupations (unweighted)	—	—	0.093	0.116	0.093	0.096	0.084
—	Std. dev. across occupations (employment-wt.)	—	—	0.084	0.105	0.080	0.088	0.075
<i>Panel B. Employment-weighted mean normalised similarity, by Schumpeterian score</i>								
—	Schump. = 1 (127 occupations)	2,179,954	1	0.969	0.983	1.063	0.958	0.948
—	Schump. = 2 (153 occupations)	1,810,957	2	0.939	0.982	0.996	0.934	0.954
—	Schump. = 3 (88 occupations)	642,613	3	1.115	1.137	0.919	1.079	1.093
—	Schump. = 4 (36 occupations)	268,800	4	1.247	1.059	0.842	1.142	1.239
—	Schump. = 5 (25 occupations)	292,887	5	1.127	0.885	0.878	1.419	1.248
<i>Panel C. Five largest 2019 occupations with Schumpeterian score = 1</i>								
5321	Assistant nurses, home care and homes for the elderly	154,563	1	0.76	0.68	0.80	0.69	0.71
2341	Primary school teachers	127,249	1	0.95	0.96	1.15	0.95	1.13
5223	Shop sales assistants, specialised stores	125,272	1	0.96	1.17	1.16	1.10	0.91
5311	Childcare workers	114,397	1	1.05	1.16	1.18	1.08	0.98
5330	Care assistants	100,122	1	1.31	1.25	1.36	1.18	1.07
<i>Panel D. Five largest 2019 occupations with Schumpeterian score = 3</i>								
7223	Metal working machine tool setters and operators	56,154	3	1.33	1.28	0.80	1.17	1.02
7231	Motor vehicle mechanics and repairers	39,383	3	1.01	1.49	0.81	1.05	0.87
7233	Maintenance mechanics and machinery repairers	32,633	3	1.16	1.37	0.79	1.15	0.88
2211	Specialist medical practitioners	30,055	3	0.90	0.89	1.03	0.99	1.25
3112	Civil engineering technicians	29,799	3	1.20	1.08	0.75	1.14	1.26
<i>Panel E. Five largest 2019 occupations with Schumpeterian score = 5</i>								
2512	Software and systems developers etc.	88,309	5	0.90	0.88	0.79	1.57	1.29
2143	Electrical engineers	33,760	5	1.56	0.87	0.81	1.13	1.26
3113	Electrical engineering technicians	32,765	5	1.75	0.96	0.84	1.24	1.32
2511	Systems analysts and IT architects etc.	21,553	5	0.81	0.67	0.67	1.45	1.18
3512	ICT support technicians	18,805	5	1.18	1.02	1.22	1.72	1.24

Note: Cosine similarities between the Swedish SBERT embedding of each SSYK-2012 occupation description and the centroid embedding of each word bundle from Table 3. “Schump.” is the Schumpeterian score (1–5) from the main pipeline. *Panel A* reports the raw (unnormalised) centre and spread of the similarity distribution across all 429 occupations with non-missing similarities and positive employment. Cells in *Panels B–E* are normalised: each raw similarity is divided by the corresponding bundle’s all-occupation employment-weighted mean (Panel A, first row), so 1.00 equals the average occupation’s similarity to that bundle; one unweighted standard deviation corresponds to roughly 0.23–0.31 in normalised units, depending on bundle. *Panel B* aggregates occupations by their integer Schumpeterian score; the cells are employment-weighted means within each score. *Panels C, D and E* list the five largest 2019 occupations with Schumpeterian scores of 1, 3 and 5 respectively; occupation titles are English translations of the Swedish SSYK-2012 titles. In Panels B–E the highest value in each bundle column within the panel is shown in bold. Reading down the ICT and Science columns of Panel B, similarity rises with the Schumpeterian score; Communication falls; Mechanical peaks at score 3. *Source:* LISA 2019 (SSYK-2012 occupation descriptions); embeddings from the KBLab *sentence-bert-swedish-cased* model.

C.2 Is persistence an artifact of HISCO?

Because HISCO is a fixed historical classification, one might worry that it has no room to represent occupations that did not exist when it was designed, and that new work is therefore absorbed into existing codes—making persistence an artifact of the instrument rather than a feature of the labor market. We test this by holding the exercise fixed and varying only the identifier. Figure A11 reports the share of employment in occupations new since 1960 under two definitions of what counts as the same occupation: the 5-digit HISCO code used throughout the paper and the raw Swedish occupational code as Statistics Sweden recorded it.

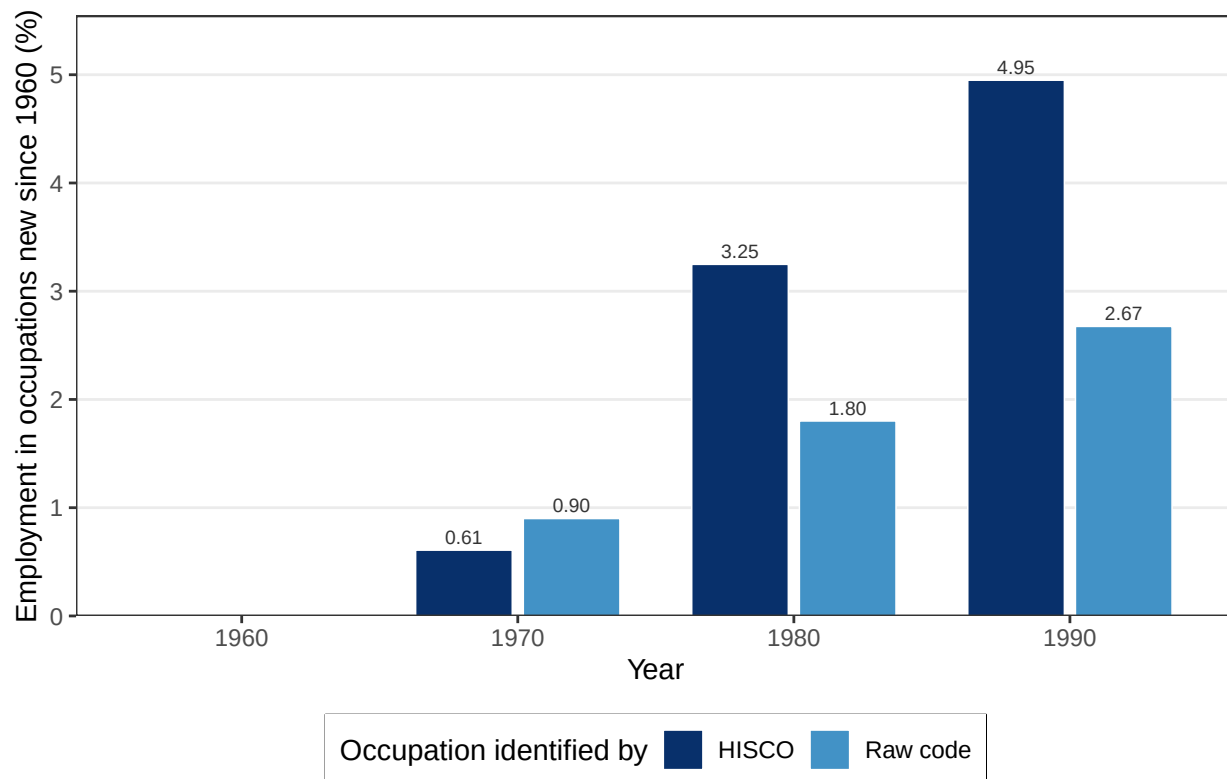


Figure A11: Occupational Entry under Two Identifiers

Note: Share of employment in occupations new since 1960, holding the base year, the 50-worker entry threshold and the set of years fixed, and varying only how an occupation is identified: 5-digit HISCO; the raw Swedish occupational code (Yrke60/70/75, FoB80). Vintages are cumulative. *Source:* FOB 1960–1990 with the occupational schemas; authors’ calculations.

We restrict the comparison to 1960–1990. This is the only stretch in which the raw codes remain within a single classification family: the introduction of SSYK in 2001 renumbers every occupation, so any figure that crosses it measures the renumbering rather than occupational entry. The window is not a permissive one—it is precisely the period in which third-industrial-revolution occupations are entering fastest.

We show that using the raw codes produces more stickiness than with HISCO, that accounts for qualitative changes to the actual strings.

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