What makes new work different from more work?[*]

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Abstract

We study the role of expertise in *new work*—novel occupational roles that emerge as technological and economic conditions evolve—using newly available 1940 and 1950 Census Complete Count files and confidential American Community Survey data from 2011–2023. We show that new work is systematically distinct from simply *more work* in existing occupations in four respects. First, it attracts workers with distinct characteristics: new work is disproportionately performed by younger and more educated workers, even within detailed occupation-industry cells. Second, new work commands economically significant wage premiums that persist beyond workers' initial entry into new work, consistent with returns to scarce, specialized expertise rather than temporary market disequilibrium. Third, these premiums decline across vintages as expertise diffuses, with 'newer' new work commanding larger premiums than older new work. Fourth, the emergence of new work can be traced to specific demand shocks in particular locations and time periods, suggesting that expertise formation responds systematically to economic opportunities. These findings suggest that new work serves as a countervailing force to automation-driven job displacement not merely by creating additional employment, but also by generating new domains of human expertise that command market premiums. This expertise-based mechanism helps explain both the expanding variety of work activities across decades and the historical resilience of the labor share.

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> The theory of the Lump of Labour will be seen to rest upon the utterly untenable supposition that a fixed amount of work exists, which has to be done, and will be done, irrespective of the conditions under which work is done, and, in particular, irrespective of the efficiency of the labour employed; and that, the more work is done by any one workman, the less work remains to be done by all other workmen.
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> – David F. Schloss, *The Economic Review*, 1891

1 Introduction

Public concern that technological advances will reduce the demand for labor has been pervasive for centuries. The economics profession's systematic dismissal of these concerns also has a substantial history. In 1891, British economist David F. Schloss coined the pejorative term "theory of the Lump of Labour" to describe what he characterized as the "untenable supposition that a fixed amount of work exists... and that, the more work is done by any one workman, the less work remains to be done by all other workmen" (Schloss, 1891). While Schloss offered no explicit justification for this argument, the rationale is built into modern axiomatic consumer theory: because rising labor productivity increases consumer purchasing power, and because consumer demand for goods is insatiable, labor demand is unbounded. This theory implies that there will always be *more* work.

This argument is not as ironclad as it may appear. As macroeconomists have long understood, labor demand rises in proportion to productivity only if labor's income share is constant. This constancy was apparent for much of the 20th century, as famously documented by Kaldor (1961), but the labor share in many industrialized countries has registered a substantial decline since the early 2000s (Elsby et al., 2013; Karabarbounis and Neiman, 2014; Dao et al., 2017; Cette et al., 2019; Barkai, 2020; Kehrig and Vincent, 2021; Karabarbounis, 2024), with the steepest fall—approximately 6 percentage points, or 10%—detected in the United States.[1] A fall of this magnitude is difficult to rationalize in neoclassical production models, requiring that capital and labor are much more substitutable than is generally believed (Acemoglu and Restrepo, 2018b). Indeed, the general macroeconomic consensus is that labor and capital are gross complements (Oberfield and Raval, 2021; Jones and Liu, 2024).

Contemporary task models potentially offer a clearer and more plausible interpretation of this rapid fall in labor share (Autor et al., 2003; Acemoglu and Autor, 2011; Acemoglu

[1] Data from the St. Louis Federal Reserve Bank indicate a roughly 10 percent decline in the labor share in the nonfarm business sector between 2000 and 2020, seen in this plot.

and Restrepo, 2018a,c, 2019). Simultaneously, they rationalize the concern that the public has voiced for centuries. In standard production functions, capital smoothly substitutes for labor along convex production isoquants, so rapid falls in the labor share are unlikely. In task models, by contrast, capital may serve as a perfect substitute for labor in a specific set of tasks, and technological advances that expand this set can effectively diminish labor's share one-for-one. This makes the possibility of rapid labor displacement readily conceivable, and concrete examples of such displacement abound. Between 1920 and 1940, for example, the monopoly operator of the U.S. telephone network, AT&T, implemented a staggered adoption of mechanical telephone switching technology across U.S. cities. As cities made the technological transition, their local telephone operator employment fell by 50 to 80% within a decade (Feigenbaum and Gross, 2024).

By conceptualizing the interplay between labor and capital as one of direct competition over a bounded set of tasks, task models open a radical possibility: asymptotic task encroachment (Susskind, 2020). Here, technological advances enable capital to subsume an ever expanding set of tasks, eventually driving the labor share to zero.[2] Evidence from both industry and firm-level analyses confirms a direct link between technology adoption and falling labor share in many settings (Autor and Salomons, 2018; Acemoglu et al., 2020; Acemoglu and Restrepo, 2022; Restrepo, 2023), though recent literature also provides prominent counterexamples (Curtis et al., 2021; Hirvonen et al., 2025). Contrary to Schloss (1891)'s dismissal of the lump of labor fallacy, task models recognize that technological advances *can* diminish labor demand. This is not because there is a "fixed amount of work to do", but rather because technological advances can make capital more cost-effective than labor in performing the tasks that need doing.[3]

Without further extension, the task framework makes two counterfactual predictions. First, because automation is unlikely to run in reverse, the labor share should trend mainly downward. In reality, labor's share of national income has risen and fallen across decades (Blanchard, 1997). Second, the framework predicts that as automation proceeds, labor will be shunted into an ever-narrowing scope of activities. But casual observation and historical evidence suggest the opposite: as employment in labor-intensive sectors such as agriculture, textiles, and mining has eroded, the scope and variety of labor-demanding activities has expanded, for example, in medicine, software, electronics, health care, finance, entertainment,

[2] More precisely, the wage per efficiency unit of labor is driven down to the (perpetually falling) capital rental rate, which may not be a subsistence wage.

[3] This parallels the argument in Leontief (1983) that "...the role of humans as the most important factor of production is bound to diminish-in the same way that the role of horses in agricultural production was first diminished and then eliminated by the introduction of tractors."

recreation, personal care, and other domains (Atalay et al., 2018, 2020; Autor et al., 2024). Something else is needed to explain fluctuating labor share and expanding work variety.

That missing ingredient—and the subject of this article—is *new work*, meaning novel job tasks that demand human labor. The formal notion of new work, along with an ingenious approach for measuring it, was introduced in a prescient paper by Lin (2011). Lin's focus was on new work as a manifestation of agglomeration economies in cities, an idea further developed in Atalay et al. (2024), Kim et al. (2024), and Kalyani et al. (2025). Building on Lin's original observations, papers by Acemoglu and Restrepo (2018c), Acemoglu and Restrepo (2018a), and Acemoglu and Restrepo (2019) linked the concept of new work to the task model. A key insight of these papers is that new work provides a countervailing force to automation: while automation erodes labor's share through task displacement, new work reinstates labor's share through new task creation. This task-reinstating role of new work potentially addresses the *first* puzzle above: fluctuating labor share.

This article explores the *second* puzzle addressed by new work: the expanding variety of work. By definition, the variety of work is fixed until new varieties emerge. New work self-evidently plays this role. But the economic point goes deeper. Expanding variety is, we believe, fundamental to understanding why new work offsets the task-eroding effects of automation. New work reinstates labor share because it demands novel human expertise (capability, skill, human capital, know-how) to perform specific job tasks that were not previously used in production. This mechanism is distinct from canonical models of Skill-Biased Technological Change (SBTC), where factor augmenting technologies increase the marginal product of skilled workers without directly changing the forms of work they do (Katz and Murphy, 1992; Katz and Autor, 1999; Krusell et al., 2000).[4]

Not all human expertise has labor market value; possessing surpassing expertise in an obscure hobby may generate no market reward. Expertise must meet two criteria to command market value: it must be an input into the production of a good or service that itself has market value; and it must be scarce (Autor, 2024; Autor and Thompson, 2025). If expertise is necessary but not scarce, or it is scarce but not necessary, then its market value will be minimal. New work meets both criteria—necessity and scarcity. Because new job categories are recognized by the U.S. Census Bureau only when a sufficient number of workers reports that they perform them, we infer that these new job categories provide market-traded products or services. And by dint of their novelty, we expect that the expertise required to perform these new

[4]As Katz and Autor (1999) discuss, the canonical model of SBTC allows for 'extensive margin' technological changes, which directly shift tasks among skill groups, which can be read as a form of new task creation. But this mechanism has not featured in canonical analyses of SBTC.

categories of work is scarce, at least in the short run.

This paper studies the role of expertise in new work. We build on prior scholarship that has explored the prevalence of new work (Atalay et al., 2020; Autor et al., 2024), characterized its geographic distribution (Lin, 2011; Kim, 2022; Atalay et al., 2024; Kim et al., 2024; Kalyani et al., 2025), identified factors that affect its emergence (Autor et al., 2024; Kogan et al., 2024), and considered its role in offsetting the labor-share eroding effects of automation (Acemoglu and Restrepo, 2018c, 2019). This paper examines five implications stemming from the observation that new work demands novel, scarce expertise:

1. Since new work is distinct from preexisting work, it may be undertaken by workers with different observable characteristics, both across and within occupations. If performing new work entails investing in new skills, younger workers and those with higher levels of formal education may be relatively better positioned to do so.

2. Reflecting its scarcity, new work should command a wage premium. This premium should be evident even conditional on detailed occupation and industry categories and standard measures of demographics and human capital. This scarcity premium is potentially higher for new work variations that require mastering emerging technologies versus those that merely tap into a new source of consumer demand.

3. Reflecting the skill investment accompanying the mastery of new work, those who perform it should earn quasi-rents that persist beyond their moment of entry into new work.

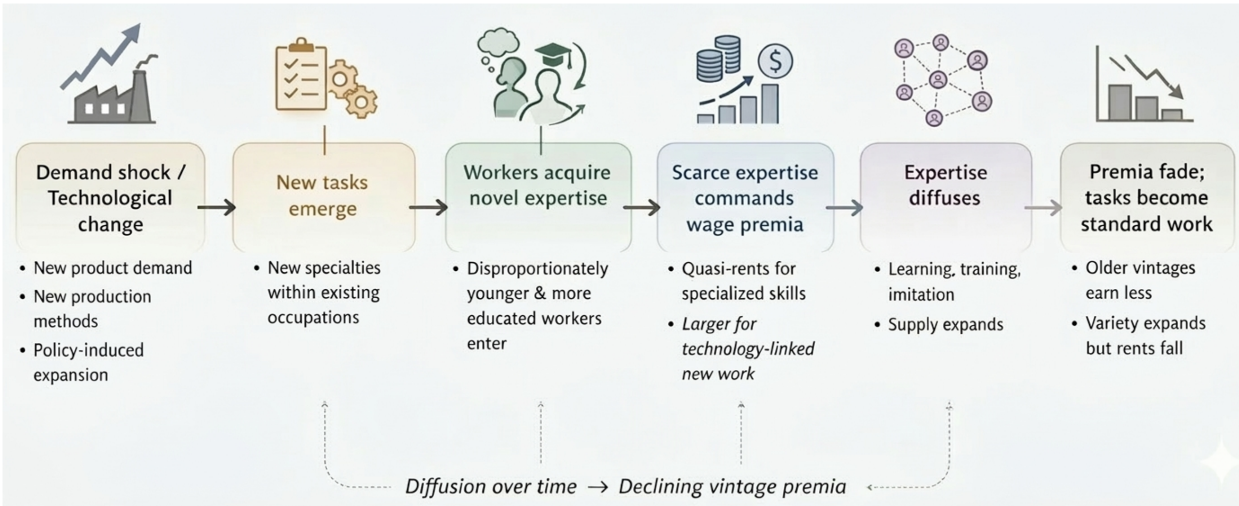
4. Because the scarcity of expertise required for new work is likely transitory—reflecting the disequilibrium of novelty—the premium to new work should generally decline across vintages. This is, 'newer' new work should command a larger premium than 'older' new work. But the new work premium is likely to be more durable in forms of new work that require greater expertise acquisition.[5]

5. New work should arise in occupations, time periods, and locations where new sources of labor demand create opportunities for job specialization and expertise formation.

The schematic below illustrates the conceptual framework underlying these predictions, tracing the flow from demand shocks that create new work, through the supply response of worker expertise, to the emergence and eventual dissipation of scarcity rents.

[5]In contemporaneous work, Hassan et al. (2026) offer a macroeconomic model in which new technologies instantiate demand for new expertise that commands a scarcity premium. This premium fades as knowledge diffuses and technologies become routinized.

Conceptual schematic: New work, expertise scarcity, and wage premia



Our empirical analysis exploits two almost-untapped data sources. A first is the newly-released 1950 Census IPUMS Complete Count files, which we combine with the (longstanding) 1940 Census Complete Count data set. Using the individual job write-ins in these data sets, we characterize employment in new work cross-sectionally in both decades, and we exploit longitudinal linkages across decades to analyze worker transitions across new and preexisting work.[6] Our second data source is the confidential American Community Survey (ACS) for the years 2011 through 2023. The ACS enables for the first time the study of new work in contemporary representative worker-level data.[7] Our analysis complements Martin-Caughey (2021, 2023), who use these write-in data to analyze gender and income differences in self-reported job duties within and across occupations.

Section 2 documents data sources and methods and leverages the person-level occupational write-ins to estimate the prevalence and occupational locus of new work in aggregate, across the occupational distribution, and in historical and recent data. This analysis improves on earlier efforts that rely on the relative frequency of occupational titles as proxies for new work employment rather than direct, person-level new work write-ins. We then test the implications above. Section 3 characterizes the attributes of those employed in new work relative to the general workforce. Section 4 estimates the wage premium to expertise in new

[6] Autor et al. (2024) use the 1940 Census Complete Count to characterize new work in a single cross-section. Using the 1950 Census Complete Count file, this paper extends this exercise to 1950 and adds the linked longitudinal component.

[7] Innovative studies of new work in contemporary data exploit job postings (as distinct from worker data) from the Burning Glass Institute and other sources (Deming, 2017; Atalay et al., 2020; Acemoglu et al., 2021; Atalay et al., 2024) or use proxies of new work in Census data and ACS data (Kim, 2022; Kim et al., 2024) rather than person-level self-reports as used here.

work from three perspectives: relative to preexisting ('old') work across multiple decades; across vintages within a decade, contrasting the premium to the 'newest' work relative to older new work; and within workers over time, examining the link between past experience in new work and current earnings. Building on recent study of the long-term labor market consequences of WWII era manufacturing plant construction data (Garin and Rothbaum, 2025), we show in section 5 that the geography, timing, and (broad) sector in which new work emerges can in some instances be traced directly to demand shocks.

Key Terms

New work refers to occupational titles that appear for the first time in the Census Bureau's decennial occupation list, the Census Alphabetical Index of Industries and Occupations (CAIO).

Vintage refers to the period in which a new occupational title was introduced to the Census Bureau's occupation list. For example, *Artificial Intelligence Specialist* was first added in the 2000 edition occupation list, and is assigned to the 2000 vintage. *Cybersecurity analyst* was introduced in 2018, and assigned the 2018 vintage.

Technology-linked new work includes titles whose emergence is associated with technological change (e.g., *Wind turbine erector*, *Database administrator*). In contrast, *Other new work*, consists of titles not associated with technological change (e.g., *Drama therapist*, *Conference planner*).

2 New work, directly observed

2.1 Occupation-level new work measurement

A longstanding barrier to measuring the prevalence of new work is the lack of detailed occupational data in representative U.S. Census files. Workers' self-reported occupations (write-ins), which are needed to determine their employment in new work, are not directly available in Census public use files. Instead, these files report workers' employment using 3-digit Census occupational codes. These codes are based on individual write-ins, but they sacrifice the detail needed for this analysis.

To overcome this limitation, researchers following Lin (2011) have relied on imputation, estimating employment in new job titles by multiplying two factors: (1) the share of new detailed occupational titles within each 3-digit Census occupation, and (2) total employment in that occupation. The new-title share comes from the Census Alphabetical Index of Industries and Occupations (CAIO) (U.S. Census Bureau, 2018), calculated as the ratio of new titles to total titles within each Census occupation. The Census Bureau maintains the CAIO, a detailed standardized list of occupational titles, to assist in coding write-in responses into Census occupational code categories. The index is regularly updated to include new job titles as they become more prevalent among write-ins. The addition of these new titles can be used to impute the prominence of new work within an occupation. For example, consider a 3-digit occupation that contains 200 detailed occupational titles. If 10 of these titles are newly added to the CAIO, the Lin (2011) approach would estimate that 5% of employment in that occupation represents new work.

While the qualitative validity of this imputation method is corroborated by Lin (2011) and Autor et al. (2024), it has three clear limitations. First, it neglects the dynamics of employment in new work. The proportionality assumption implies that employment in new work categories reaches steady state immediately after new titles emerge. More plausibly, employment in new titles accumulates gradually, and may subsequently fade if the category proves ephemeral. Second, the imputation approach is silent on the geography of employment in new work. While some analyses sidestep this issue by assuming that employment in new work within 3-digit occupations is constant across geographies (Lin, 2011; Kim, 2022; Kim et al., 2024), both theory and (non Census-based) evidence suggest that new work is more prevalent in cities (Lin, 2011; Atalay et al., 2024; Kalyani et al., 2025). Finally, absent direct observation, it is infeasible to compare the demographics and earnings of workers employed in new work with those employed in longstanding work.

2.2 Person-level new work measurement

We surmount these limitations by analyzing person-level occupational write-ins from both the historical 1940 and 1950 IPUMS full count files (CCC, Ruggles et al. 2024) and the confidential contemporary American Community Survey (ACS) for 2011–2023, analyzed in the Federal Statistical Research Data Center.[8]

Crucially, both datasets contain verbatim occupational write-in responses, which provide more granular detail on occupation titles than Census occupation codes alone. We restrict the sample to employed individuals ages 16–64 with non-missing occupation codes and positive earnings, excluding unpaid family workers and military occupations. Because our new work classification relies on the occupational write-in fields, we further drop records with missing write-ins. In 1950, education and earnings are observed only for the 20% of respondents

[8] ACS survey data from 2012 and 2013 are excluded from the analysis due to the absence of person weights (2012) and respondent occupation write-in data (2013).

who received a longer "sample line" survey. Therefore, analyses using wages or education information are limited to these observations. The 1950 earnings field has documented errors leading to systematic underestimation of earnings. To imperfectly account for these recording errors, we trim the bottom 10% of earnings within each Census occupation. Finally, we link individuals across 1940 and 1950 using the IPUMS MLP crosswalk to form a longitudinal person-level panel containing approximately 35% of worker observations (Ruggles et al., 2025). Appendix A.1 provides further details on sample construction.

Our person-level measure of new work links each respondent's occupational write-in to the closest CAIO title within the same three-digit Census occupation code (Autor et al., 2024). For the historical samples, we first encode CCC write-ins and CAIO titles as word embeddings, then compute pairwise match scores for each write-in and CAIO title within the same year-by-occupation-code cell. These scores are the cosine similarity between the embedding vectors of the occupational write-in and CAIO title, where higher values indicate greater semantic similarity.

For the contemporary ACS (2011–2023), we mirror this procedure using character-based fuzzy string matching in place of embeddings.[9] The match scores generated in this procedure represent the n-gram overlap between an occupational write-in and CAIO titles, where higher values indicate more shared substrings. In both cases, the occupational write-in is assigned to the highest-scoring matched title. As we expect higher rates of employment in preexisting work, we impose a greater match score threshold for links to new titles. Matches to new CAIO titles that are below 0.7 in the historical sample and 0.5 in the contemporary sample are recoded as existing work, leading to a more conservative estimate of new work. Appendix A.2 provides further details on the data and matching procedure.

New CAIO titles are organized into decadal "vintages", reflecting the decade in which the title was added to the index. In the historical analysis, we link 1940 CCC respondents to the 1940 CAIO vintage and 1950 CCC respondents to the 1940 and 1950 CAIO vintages of new work. A respondent is classified as employed in new work if they are matched to a new title with a match score above the threshold. In the historical data, new work reflects employment in titles that have emerged since 1930. In the contemporary analysis, we link each ACS respondent to the 1980, 1990, 2000, and 2018 CAIO vintages of new work, consolidating 1990 with 2000 due to sparse, administratively driven updates. In these data, new work refers to job titles that have emerged since 1970. In our vintage-specific analysis in section 4.2, workers who are matched to multiple new CAIO titles across vintages are

[9] We use fuzzy matching rather than embeddings due to data and model constraints in the Federal Statistical Research Data Center where the ACS linkage is performed.

assigned a unique vintage by selecting the match with the highest similarity score.

2.3 Descriptives of person-level new work

Employment in new work is prevalent. The ACS data provide to our knowledge the first representative enumeration of new work employment in 21st century data. These data show that in 2011–2023, 18.3% of workers are employed in jobs introduced since 1970.[10] Using the 1950 Census complete enumeration file, we find that 7.2% of workers in 1950 were employed in new work introduced after 1930, as detailed in Appendix Table A1. Noting that the time window for new work emergence covered by the contemporary data (five decades) is 2.5 times that of the historical data (two decades), the decadal flow of new work appears roughly equivalent in these two time intervals ($7.2\% \times 2.5 = 18.0\%$). This comparison should not be taken to imply that new work is equally prevalent in historical and contemporary data, however, since the accumulation of employment in new work is unlikely to be linear.

Figure 1 reports the occupational distribution of employment in new work in both time intervals across twelve exhaustive, mutually exclusive occupational categories comprising U.S. civilian employment. These occupations are ordered from lowest to highest average annual earnings (based on means from the ACS data), with farm and mining occupations on the left-hand side and managerial occupations on the right. Visible in this figure is the sharp shift in the locus of new work from middle-paid to high-paid occupations across these two eras, as documented by Autor et al. (2024). In 1950, more than four in ten workers employed in new work titles were found in either Production or Clerical and administrative support occupations, which were roughly in the middle of the earnings distribution. In the most recent decade, by contrast, more than four in ten workers in new job titles are in the two highest-paid occupational categories, Professional and Managerial occupations.

The genesis of new work is varied. While many new titles are plausibly associated with new or evolving technologies (e.g., “Airplane engineer” in 1950, “Engineer computer application” in 1970, and “Artificial intelligence specialist” in 2000), others appear to reflect changing tastes, income levels, and demographics (e.g., “Art critic” in 1950, “Mental health aide” in 1970, and “Conference planner” in 1990). This diversity of origins is likely accompanied by a diversity of expertise requirements. For example, it plausibly requires a larger human capital investment to become an Artificial intelligence specialist than a Conference planner.

At some risk of oversimplification we further distinguish between new occupational titles that

[10] Because the last release update to the CAIO corresponds to the 2018 ACS, we do not capture new titles introduced between 2019 and 2023.

are plausibly attributable to novel or evolving technologies and those whose origins may lie elsewhere. To identify the subset of technology-linked new titles, we apply OpenAI's GPT4o large language model (LLM), with the prompt given in Appendix A.2. We validate the tech-related LLM classification with a manual human audit of a random subsample (where we find 95% human agreement with the model labels), and we also compare the share of technology-linked new titles with occupational augmentation patent links in Autor et al. (2024), which reveals a significantly positive relationship. The LLM classifies a little over half of new titles as technology-linked. See Appendix A.2 for further details.

Panel B of Figure 1 reports the share of new work classified as technology-related in each broad occupation. There is substantial commonality in the prevalence of technology-related new work across decades. Occupations in which new work is predominantly technology-related include Production, Construction, Farming and mining, and (logically) Technicians. Occupations with persistently low technology-related work shares include all three categories of services (Health, Personal, and Cleaning and protective), and managerial occupations. By our metric, the technology-intensiveness of new work has declined in Farming & mining, Transportation, and Clerical & administrative support. It has risen sharply in Professional occupations, and Sales occupations. Reflecting the migration of new work from production and clerical occupations to professional and managerial occupations, we estimate that the overall share of new work that is technology-related is lower in contemporary data than in 1950.[11] Despite its coarseness, this classification of technological origins is potentially useful for understanding how expertise requirements and the associated new work premia differ across broad categories of new work. We explore these distinctions in section 4.

As noted above, the 2011–2023 ACS data provide the first enumeration of new work employment derived from contemporary, representative microdata rather than occupation-level imputations. Appendix Table A2 compares observed values of employment in new work with imputed values based on new title shares following Lin (2011) and subsequent work. In making this comparison, we highlight that our observed values are likely conservative relative to imputed estimates because the imputation approach assumes that employment in new work reaches its steady-state immediately upon emergence. While this proportionality approximation may hold over the longer run, it is likely an overstatement for the newest cohorts of titles.

Comparing observed and imputed values in Appendix Table A2 reveals three patterns. First, the imputation approach overstates direct write-in based estimates of employment in new work. It implies that approximately one in three workers is currently employed in new work,

[11] As reported in Appendix Table A1, this share falls from 46% (3.34%/7.23%) to 33% (5.96%/18.31%).

while the directly measured value is closer to one in five. Second, the disparity between imputed and observed values differs substantially across occupational categories: the largest proportional overestimates occur in Sales, Farming and mining, and Transportation; the imputation is close to exact for Technicians; and the imputation is too conservative only in the case of Health services. Finally, the correlation between the imputed and observed distributions of new work *across* occupations ($\rho = 0.91$) is substantially higher than correlation between the imputed and observed new work shares *within* each occupation ($\rho = 0.51$).

These comparisons highlight the limitations of using occupational new title shares to impute employment in new work. But they do not yet exploit the key advantage of direct person-level observation of employment in new work, which is the ability to characterize who performs new work, to observe transitions between preexisting and new work, and to estimate the expertise premium in new work.

3 Who performs new work?

Who performs new work? Previous studies that measure new work using representative Census, CPS, and ACS data (e.g., Lin 2011; Autor et al. 2024; Kim et al. 2024) estimate the characteristics of those employed in new work by calculating which demographic groups are overrepresented in occupations with a larger share of new titles. Alongside the imprecision of such imputations, this approach cannot distinguish how workers employed in new work differ from those employed in preexisting work within detailed occupation categories (e.g., within Computer and information systems managers or within Electrical power-line installers and repairers). Our direct observation of employment in new work enables this granular analysis.

Table 1 presents results from regressing an indicator for individual new work employment on worker characteristics across six dimensions: education, age, gender, race, self-employment status, and rural versus urban location. We classify educational attainment into five categories: less than high school, high school diploma or GED, some college, bachelor's degree, and more than a Bachelor degree.[12] Age is grouped into three categories: 16–29, 30–54, and 55–64. We identify four racial and ethnic groups: white, Asian, Black, and Hispanic workers.[13] The reference category in Table 1 is white male workers aged 16–29, with a high school degree, who are not self-employed and live in a rural area. Results for 2011–2023 (capturing new work emerging since 1970) and 1950 (capturing new work emerging 1930–1950)

[12] The 1950 Census does not allow us to distinguish workers with advanced degrees; the highest category for 1950 is bachelor's degree or above.

[13] We include a separate category for other racial and ethnic backgrounds but omit these coefficients given their limited interpretability.

are presented side-by-side to facilitate comparison.

Employment in new work is not evenly distributed across demographic groups in either period. The incidence of new work rises monotonically with educational attainment: this pattern persists even within detailed occupational categories (columns 2 and 5), and is robust to the inclusion of a full set of detailed industry and county dummies (columns 3 and 6). In our preferred specification with the full set of controls, workers with advanced degrees are 2.9 percentage points more likely to be employed in new work than high school graduates over 2011–2023—a substantial difference relative to the overall new work employment rate of 18.3 percent. Similarly, in 1950, workers with a bachelor degree or higher are 1.3 percentage points more likely to be employed in new work than high school graduates, compared to a mean new work employment rate of 7.2%. Thus, although the occupational distribution of new work has changed substantially, more educated workers consistently attain a disproportionate share of new work, both overall and within occupational categories.

Logically, it is not only the prevalence of new work that differs across education groups but also its occupational locus. Comparing the occupational distribution of new work between workers with at least four years of college education versus those with less, Appendix Figure A1 documents that new work among workers who attended college for at least four years are overwhelmingly concentrated in Professional and Managerial occupations—though notably, new work in Technical occupations is a much larger category in contemporary than historical data. Among workers with fewer than four years of college exposure, Production and Clerical and administrative support occupations account for more than 40% of new work employment in 1940–1950. In contrast, these categories jointly comprise less than 25% of new work employment among this education category in contemporary data, and are now exceeded by new work employment in Health services and Personal services. The movement of new work from among less-educated workers from middle-skill production and administrative support occupations towards typically lower-paid services mirrors the changing overall locus of employment among non-college workers (Autor and Dorn, 2013).

The age pattern of employment in new work is also consistent across periods: younger workers, below age 30, are most likely to be employed in new work, workers ages 55–64 are least likely to be employed in new work, and workers ages 30–54 fall in between. . These education and age gradients may reflect the greater ease with which more educated and younger workers acquire novel skills and expertise demanded in new work.

Beyond schooling and age, we observe substantial demographic differences in the likelihood of employment in new work that are qualitatively similar across the time periods. Holding education, age, occupation, industry, and county groups fixed, whites, women, non self-employed, and urban workers are most likely to be employed in new job titles. The urban concentration of new work corroborates prior findings by Lin (2011) and Kim et al. (2024), who infer from occupation-level new title shares that new work is more prevalent in cities. Table 1 confirms this inference and further shows that, even within new work-intensive occupations (and within counties), the incidence of new work is higher still in urban areas.

The concentration of new work among highly-educated, white, young, and urban workers—attributes typically associated with higher earnings—suggests that new work may offer an earnings premium. We assess this supposition next.

4 The value of expertise in new work

The essential attribute that distinguishes new from preexisting work in our definition is that new work demands novel human expertise, meaning specialized knowledge that was not previously in demand. By dint of its novelty, the expertise required in new work may not be abundant at the time that demand emerges. If so, that expertise should command a wage premium in the short to medium run (Hassan et al., 2026). Whether this premium is enduring will depend both on the persistence of demand and the elasticity of supply. If the relevant expertise is readily acquired at low cost, we expect the premium to be transient. If it requires a significant skill investment (Mincer, 1958) or draws on capabilities that are intrinsically scarce (e.g., rare prowess in athletics, intellect, leadership, or creativity), then the premium may be more durable. We assess the new work wage premium in three steps: by estimating the average new work premium in contemporary and historical data; by exploring the durability of this premium across vintages of new work (i.e., older versus more recent vintages); and by analyzing wage changes of workers transitioning between preexisting and new work and vice versa.

4.1 The contemporary and historical new work premium

To assess whether workers employed in new work receive higher wages than observably similar workers in preexisting work, we fit cross-sectional OLS regressions of the following form:

$$\ln w_{it} = \alpha_t + \beta \text{New}_{it} + x_i' \pi + \gamma_j + \lambda_k + \kappa_c + \varepsilon_{it} \ , \tag{1}$$

where the dependent variable is the log annual earnings of worker i in year t, and New_{it} is an indicator variable equal to one if i is employed in new work in that year. All models include year fixed effects α_t. Absent other controls, the coefficient $\hat{\beta}$ estimates the mean log wage gap between workers employed in new versus preexisting work. Additional controls greatly sharpen this contrast. Following the format of Table 1, the vector x_i contains a detailed set of demographic controls including education, age and age squared, gender, race, self-employment status, and urban residential location. Some estimates further include 3-digit occupation effects (γ_j), 3-digit industry effects (λ_k), and county effects (κ_c).

In both recent and historical data, workers employed in new job titles earn a wage premium. As shown in panel A of Table 2, the unconditional new work wage premium is 15.6 log points in 2011–2023 and 9.0 log points in 1950. Logically, most of this differential stems from the greater prevalence of new work in middle-wage and higher-wage occupational categories. Column 2 accounts for these occupational composition differences by including a full set of 3-digit Census occupation dummies. The new work premium is robust and remarkably comparable across periods at around 2.7 log points in both 2011–2023 and 1950. Adding the full set of demographic controls from Table 1 only modestly affects these point estimates: the estimated new work premium is 2.5 and 2.4 log points in contemporary and historical data, respectively. This stability of point estimates is noteworthy given that these demographic variables are strong predictors of entry into new work, as shown in the prior table. The modest impact of demographic controls likely reflects offsetting correlations with wages: while some characteristics associated with new work entry (such as higher education) predict higher wages, others (such as younger age) predict lower wages, leaving the net premium largely unchanged.

The final column of Table 2 adds a full set of 3-digit industry dummies and U.S. county dummies. Conditional on this exhaustive set of controls (there are >3K counties), the new work premium is estimated at 1.8 log points in contemporary data and 1.4 log points in historical data.

We hypothesized above that technology-linked new work might command a larger expertise premium. Panel B of Table 2 confirms this prior. The unconditional premium in technology-linked new work is many times that in other new work titles (i.e., the complementary set), but this mostly reflects that technology-related new titles disproportionately reside in middle-wage and higher-wage occupational categories. Column 2 accounts for these differences with a full set of 3-digit occupation dummies. Even within detailed occupation categories, technology-linked new work premium is 8.3 log points in 2011–2023 and 6.1 log points in 1950. Conversely, the wage premium in other new work is only 0.3 log points in contemporary data and is negative (-0.5 log points) in historical data. In our preferred specification in column 4, which includes demographics, and occupation, industry, and county dummies, we estimate a premium in technology-linked new work that is roughly four times the corresponding other new work premium in both periods. Specifically, the technology-linked new work-premium is 3.8 and 2.2 log points in contemporary versus historical data, as compared to 1.0 and 0.6 log points in other new work.

In summary, those employed in new work are more educated and higher-paid, even conditional on other worker observables, than those employed in preexisting titles in the same detailed occupational categories, particularly for technology-linked new work. This pattern suggests that new work may be more specialized and expertise-intensive than preexisting work. These cross-sectional regressions cannot, of course, fully account for unobserved selection into new work, and hence leave open the possibility that workers employed in new work would counterfactually earn the same premium if they performed preexisting work—though this would leave a puzzle as to why workers with unobservably high earnings potential systematically report employment in new job titles. In section 4.3, we find using longitudinal data that wage levels are relatively higher among workers who previously held new work, even conditional on current participation in new work, suggesting that skill acquisition rather than selection in part drives these returns.

4.2 When new work gets old

Viewed from a single vantage point, workers will be employed in multiple vintages of new work. In the contemporary ACS data, observable vintages include titles introduced between 1970 and 1980, 1980 and 2000, and 2000 and 2018.[14] This cross-vintage variation provides an opportunity to assess whether the new work premium persists as new work transitions from novel to established.

We test the persistence of new work wage premia across vintages by replacing the new work dummy in (1) with a set of interaction terms between a worker's employment in new work and the vintage in which that title was introduced. Fit to data for 2011–2023, Figure 2 plots the resulting coefficients measuring the wage premium of being employed in a job introduced in each period relative to jobs that existed as of 1970, conditional on occupation, industry, geographic, and demographic characteristics. The x-axis denotes the time period in which the job was introduced, i.e. its vintage. The time scale on this axis is reversed (most recent to least recent vintage) to highlight that although all new work earnings premia are estimated

[14] New title updates to the CAIO were minimal in both 1990 and 2010, reflecting, we believe, administrative priorities within Census rather than underlying changes in the rate of emergence of new work. We hence combine 1990 and 2000 updates into a single 2000 cohort, and similarly combine 2010 and 2018 updates into a single 2018 cohort. Due to extensive revisions to Census occupation codes between 1970 and 1980, we cannot classify write-ins in contemporary ACS data to new titles introduced in 1970 or earlier.

using contemporary (2011–2023) data, the new work categories correspond to three distinct vintages of new work: 1970–1980, 1980–2000, and 2000–2018.

The gray line in Figure 2, corresponding to the wage premium for workers employed in all categories of new work, shows that earnings premia are higher in new work of more recent vintages. Wage differences are small for new titles introduced in 1970–1979 (-0.82 log points), moderate for those introduced in 1980–1999 (1.57 log points), and substantially larger for titles introduced in 2000–2018 (4.72 log points). Appendix Table A3 reports the coefficients and alternative specifications with increasingly restrictive sets of controls.

These patterns are consistent with the hypothesis that the new work premium fades as new work ages. It is not possible, however, to distinguish cohort from age effects in the new work premium—specifically, whether older new work paid more when it was newer, or whether instead the "newest" new work is simply intrinsically higher paying. One exercise that may shed light on this interpretational point is to estimate the vintage premium in new work separately for technology-linked versus other new work. If the new work premium is lower in older vintages of new work in both technology-linked and other new work, this would be most consistent with premium fade-out—since it's hard to see why newer vintages of technology-linked and non-technology-linked new work would both be intrinsically higher paying than older vintages.

To implement this test, we partition new occupations into technology-oriented and non-technology-oriented categories, and re-estimate our augmented specification separately for each. The blue and orange series in Figure 2 report this exercise. In both technology-related and non-technology-related new work, the premium is monotonically increasing in recency. For the most recent cohort of new work (introduced between 2000 and 2018), the technology-oriented new work premium is 9.13 log points, while in the complementary category of new work, it is approximately 3.03 log points. For vintages introduced between 1980 and 2000, the premia are less than half as large: 3.89 log points for technology-related new work, and 0.86 log point for other new work. For the oldest vintage of new work, introduced between 1970 and 1980, the technology-related new work premium is essentially zero, while the non-technology-related new work premium is -1.34 log points.

That the scarcity premium fades across vintages for both forms of new work is consistent with the interpretation that this premium reflects transient skill scarcity rather than a permanent feature of new occupations. The higher initial premium for technology-driven new work, combined with its steeper decay, accords with Deming and Noray (2020)'s finding that technology-related skills command high starting wages but a shallow experience premium.

Our data do not, however, allow us to distinguish how much of this decay reflects mounting obsolescence (declining demand for aging skills) versus elastic supply of expertise.

4.3 Persistence of employment and earnings in new work

Our analysis to this point has been cross-sectional, leaving two key questions unanswered: does individual employment in new work persist, and do associated wage premiums prove durable for those who perform it? We leverage data on the subset of workers linked across 1940 and 1950 Census Complete Count datasets to consider these questions. (More details on this linkage are provided in Appendix A.1.2.)

Table 3 shows the transition matrix between preexisting and new work for individual workers linked across 1940 and 1950. Among workers employed in preexisting job titles in 1940, 92.8% are also found in preexisting titles in 1950, suggesting a high persistence in existing work. Conversely, 7.2% move into new work, which is similar to the overall new work employment share of 7.5% in 1950. In contrast, one in five (19.0%) of those employed in new work in 1940 is found in new work again in the following decade, which is approximately two-and-a-half the base rate of new work in that decade. Panel A of Appendix Table A5 confirms that 1940 employment in new work predicts 1950 employment in new work. Even controlling for demographics, and occupation, industry, and county fixed effects, workers employed in 1940 new work are 6.1 percentage points more likely to be employed in new work in 1950, which is sizable relative to the baseline share of 7.5% in 1950. This persistence is not merely due to workers remaining in the same job. As shown in panel B of Appendix Table A5, the probability of a worker being employed in a 1950 vintage of new work is 1.3 percentage points higher for those previously employed in a 1940 vintage of new work, conditional on all controls. Given that the 1940 and 1950 new work vintages are non-overlapping sets and, further, that only 4.9% of workers in 1950 are employed in new work vintages introduced after 1940, this pattern indicates that a disproportionate share of those employed in new work in 1950 were employed in a different new work vintage a decade earlier.

That workers who perform new work in 1940 are disproportionately likely to be employed in new work in 1950—frequently by transitioning to a newer vintage of new work—underscores the distinctiveness of new work and the workers who perform it. We found above that workers employed in new work are observed to earn a wage premium, which we argue is attributable to specialized expertise. We probe this premium further in the longitudinal data by estimating the relationship between individual earnings in 1950 and participation in new work in both 1940 and 1950. Specifically, we fit the following model,

$$\ln w_i^{1950} = \alpha + \beta_1 \text{New}_i^{1950} + \beta_2 \text{New}_i^{1940} + \delta \ln w_i^{1940} + x_i'\pi + \gamma_j^{1940} + \lambda_k^{1940} + \kappa_c^{1940} + \varepsilon_i, \quad (2)$$

where the dependent variable is the logarithm of workers' annual wage earnings in 1950, and the independent variables of interest are a dummy for whether they were employed in new work in 1940 (New_i^{1940}) and a dummy for whether they were employed in new work in 1950 (New_i^{1950}, which includes both the 1940 and 1950 vintages of new work). In addition to 3-digit occupation dummies (γ_j^{1940}) included in all specifications, additional estimates control for a vector of worker characteristics (x_i) defined as before as well as fixed effects for workers' 1940 Census industry of employment (λ_k^{1940}) and their 1940 county of residence (κ_c^{1940}). In a final specification, we control for individuals' 1940 log wages to (partially) account for differences in earnings potential that are not captured by observables.

Estimates of equation (2) reported in Table 4 document robust and enduring wage differentials for workers employed in new work. The first column reports a model that parallels estimates of the new work premium in column 2 of Table 2 panel A2, here estimated on the subset of workers who are longitudinally matchable between 1940 and 1950 and who are employed with positive wage earnings in both periods. The precisely estimated new work wage premium in this subsample of workers is 5.1 log points, as compared to 2.8 log points in the cross-sectional sample in the earlier table. This suggests, plausibly, that the longitudinally linked sample is positively selected.

Both current (i.e., 1950) and past (i.e., 1940) employment in new work predict higher wages in 1950, as shown in column 2 of Table 4. The precisely estimated wage differential associated with past employment in new work is 2.4 log points, while the estimated wage differential for contemporaneous employment in new work in 1950 remains at 5.1 log points. The next two columns probe the robustness of these estimates by adding full demographic controls (column 3) and an exhaustive set of 3-digit industry and county dummies (column 4). The estimated wage premia for both contemporaneous and previous employment in new work remain robustly significant at 3.6 and 1.0 log points, respectively.

These observational models cannot definitively account for selection into new work based on unobservable worker characteristics. Nevertheless, as one further step to account for worker heterogeneity not directly captured by demographics, occupation, industry, and location, column 5 directly controls for workers' annual earnings in the prior decade. This covariate has a surprisingly moderate impact on the estimates. Conditional on 1940 earnings, workers who are currently or were previously employed in new work earn more in 1950. At a minimum, these findings demonstrate that participation in new work predicts differential wage growth that persists into the next decade. Our provisional interpretation is that workers gain novel expertise in new work that commands a market return.

5 Drivers of new work emergence: New work born of past policy

Left unanswered by our analysis above is what drives new work's emergence. If, as literature posits, new work is central to maintaining and augmenting the value of human expertise in the face of automation, it would be valuable to understand its origins, forecast its appearance, and potentially identify policy levers that can spur its emergence. We contribute to that goal in this final empirical section.

Prior work has primarily examined technological drivers (Lin, 2011; Acemoglu and Restrepo, 2019; Autor et al., 2024) and, to a lesser extent, aggregate demand shifts (Autor et al., 2024). Here, we document an instance where policy appears to have directly fostered the emergence of new work. The policy we study is the U.S. government's commissioning of large manufacturing plants for wartime production, built during the industrial mobilization for World War II. Garin and Rothbaum (2025) find that these investments spurred enduring regional employment growth and raised adult earnings of men born in the counties where these plants were subsequently sited. The principal channel of operation appears to have been an expansion of high-wage, blue-collar jobs in these locations (Garin and Rothbaum, 2025).

Using this same policy experiment, we assess whether WWII public-private investments spurred the emergence of new work in locations where plants were sited. If, as we hypothesize, new job specialties emerge when the labor market demands new expertise, then this is precisely a setting where we would expect new work to arise. To provide a causal test, we contrast employment outcomes in treated counties—those receiving plants—relative to a suitable set of control counties not receiving plants, both before and after WWII.

Our enumeration of treatment and control counties is drawn from Garin and Rothbaum (2025). We match this list to 1940 and 1950 IPUMS Census Complete Count files, providing high-resolution data on employment in new and preexisting work in both decades. We estimate the following model,

$$Y_c = \alpha + \beta \text{treat}_c + (x_c^{1940})'\pi + \varepsilon_c \ , \tag{3}$$

where the dependent variable represents county-level outcomes Y_c including overall and manufacturing employment growth over 1940–1950 (replicating Garin and Rothbaum 2025's findings with our data), and new work employment shares in each decade constructed from individual-level indicators. We further distinguish between all new work and technology-related new work.

Included in equation (3) are the full set of county-level controls (x_c^{1940}) applied by Garin and Rothbaum (2025), capturing 1940 county population, employment, industrial and demographic composition, wage structure, and geography. Following their approach, our treatment dummy (treat_c) indicates counties with new government-financed manufacturing plants worth \$10 million or more. Control counties exclude both treated counties and their neighbors, with major manufacturing centers omitted from both groups.[15]

We estimate equation (3) separately for 1940 and 1950, using 1940 as a placebo test since treatment occurred during the war and should not affect pre-war outcomes. Panel A in Table 5 reports estimates for total employment, while panel B focuses on the subsample of manufacturing employment, where the demand shock was concentrated.

Replicating Garin and Rothbaum (2025), we find that treated counties experienced faster employment growth over 1940–1950 (column 1).[16] Importantly, these counties not only generated *more* work, but more *new* work: column 3 shows that the share of employment in new work was 0.35 percentage points higher in treatment than control counties in 1950 (panel A), and this contrast was roughly twice as large in the manufacturing sector (panel B). Notably, there was no difference in the new work employment share in treatment relative to control counties in 1940 (column 2), supporting a causal interpretation.

In the final columns, we consider only technology-linked new work (i.e., reclassifying other new work as not new). New work emerging between 1940 and 1950 spurred by the WWII demand shock is almost exclusively technology-linked. Directly comparing the estimates in columns 3 and 5, the technology-linked new work coefficient accounts for 85 to 90 percent of the total new work coefficient, indicating that new work spurred by government-backed plant construction between 1940 and 1950 emerged almost entirely in technology-linked occupation titles. This is noteworthy since we found above that technology-linked new work typically

[15] Our analysis of 1950 data above was limited to the 20% subsample in which income and other sample-line variables are collected. We relax that restriction here because fewer than half of all U.S. counties appear in the Garin and Rothbaum (2025) analysis, most of them non-urban. Results in this section are qualitatively similar but less precisely estimated when using the 20% sample rather than the full count.

[16] Unlike other models in this table, column 1 reports a county-level first-difference equation for 1940–1950. The remaining columns are estimated separately by decade to contrast the treatment decade with the placebo decade.

has a larger and more durable wage premium than non-technology-linked new work. While the differential rate of new work emergence in treated counties is not nearly large enough to account for the full 2.5% effect of plant construction on lifetime earnings of male residents reported by Garin and Rothbaum (2025), it suggests that new work is one contributing channel to this overall effect.[17]

Garin and Rothbaum (2025) focus their analysis on men born prior to WWII in subsequently treated counties, so that any earnings gains from treatment can be confidently attributed to those who were exogenously exposed to plant construction. In an analogous (though not identical) step, we test whether employed individuals who resided in treated counties in 1940 were differentially likely to transition to new work by 1950. For this test, we fit the following linear probability model:

$$\mathbb{E}\Big[\,\text{New}_{ic}^{1950} \mid \text{Treat}_c^{1940},\, \text{New}_{ic}^{1940},\, x_i,\, \gamma_j^{1940},\, \lambda_k^{1940}\Big] = \beta\,\text{Treat}_c^{1940} + \delta\,\text{New}_{ic}^{1940} + x_i'\pi + \gamma_j^{1940} + \lambda_k^{1940}. \tag{4}$$

The dependent variable indicates whether worker i in county c is employed in new work in 1950, while our key regressor captures 1940 residence in a county that will subsequently be treated (Treat_c^{1940}). Models also control for whether workers were employed in new work in 1940 (New_{ic}^{1940}) along with the full set of worker-level variables included in equation (2), plus vectors of dummy variables for workers' 1940 occupation and industry of employment (γ_j^{1940} and λ_k^{1940}). Standard errors are clustered by county.[18] The coefficient $\hat{\beta}$ captures whether workers residing in a county in 1940 that receives additional public investment during WWII are more likely to be employed in new work in 1950.

Table 6 confirms that workers residing in 1940 counties that subsequently received federally-backed wartime manufacturing plants during the war were significantly more likely to be employed in new work in 1950 than comparable workers residing in non-treated counties. The point estimate of 0.40 (meaning a 0.4 percentage point increase) in the most complete specification in Table 6 is closely comparable to the estimated effect of plant construction on the overall new work share in treated counties in 1950 of 0.35 percentage points (Table 5, column 3). Though these coefficients are not directly comparable, their similarity suggests that much of the growth of new work in treated counties between 1940 and 1950 stems from entry into new job specialties by workers who were already present (and employed) in these counties in 1940. Viewed through the lens of place-based policies, this suggests that WWII

[17] Our estimate is conservative. The 2.5% earnings effect documented by Garin and Rothbaum (2025) primarily accrues in the decades after 1950, a period that we cannot explore with our data.

[18] In this table, we omit the wage observation requirement to maximize sample size, as wages are not analyzed here and only observed for sample line workers in 1950. Results are qualitatively identical but less precise for the smaller wage-observed subset.

plant construction spurred entry into expertise-intensive specialties among local residents.

6 Conclusions

We argue that new work is central to maintaining and augmenting the value of human expertise in the face of automation because, unlike simply *more* (preexisting) work, new work demands novel expertise that commands a scarcity premium. We document several empirical patterns supporting this interpretation, leveraging novel person-level new work measurement in both contemporary and historical U.S. data. First, compared to preexisting work, new work is disproportionately performed by younger, more educated workers, both across and within occupations, consistent with new work requiring investments in new skills. Second, new work commands a wage premium even within detailed occupations and industries, controlling for demographics and human capital. These premiums reflect quasi-rents from skill acquisition that persist beyond initial entry into new work.

Third, the wage premiums in new work decline as new work ages, consistent with the transitory nature of expertise scarcity. The premium proves more durable for technology-related new work, however, which likely requires greater expertise acquisition and therefore faces less elastic labor supply. Finally, new work emerges in locations experiencing positive demand shocks that create opportunities for job specialization and expertise formation, benefiting incumbent workers. Thus, new work serves as a countervailing force to automation not only because it expands the set of tasks performed by labor, but also because it generates new demand for scarce human expertise.

The literature on new work is, like new work itself, still emerging. We highlight several key areas for future research:

1. Regarding new work measurement, the person-level measurement we propose can be further refined. Rather than relying on new job titles collected from updates to the Census Alphabetical Index of Occupations and Industries (CAIO), new work could be identified directly by applying natural language processing tools to measure the evolution of unstructured occupational write-ins. This write-in-based approach offers finer granularity of occupational titles and mitigates concerns about discrepancies between self-described work and the Census Bureau's aggregation. This approach could flag newly emerging job specialties earlier and at a higher frequency than the CAIO-based approach. Drawing on different data sources to characterize the task content of new work beyond occupational titles or write-ins may provide deeper insight into the types of novel expertise that new work requires, and how those requirements differ over time

and across educational and demographic groups.

2. Measurement of new work emergence is so far limited to the United States: extending direct measurement to other countries would allow researchers to study how institutional differences (in education systems, labor market regulation, or industrial structure) shape the rate and character of new work creation. While there is related work from non-U.S. contexts documenting changing occupational task content (e.g., Spitz-Oener 2006), these occupational changes have not yet been directly linked to individual worker outcomes, in part because tasks are typically measured at the occupation rather than worker level.

3. Beyond measurement, important empirical questions about new work remain. First, further research could analyze how the novel expertise required to perform new work is supplied: what are the roles of educational systems, on-the-job training, and entrepreneurship? For example, Salomons et al. (2025) document how the introduction of new skills in vocational training curricula improves workers' labor market outcomes, especially when occupations are exposed to technological change. Second, beyond technological advances and the demand shocks studied so far, what additional factors drive new work emergence? For example, does changing labor supply composition also play a role (e.g., through increased immigration or rising female labor force participation)? Can government policy shape the type and geography of new work emergence, for example through industrial policy (as exemplified in the WWII era) or through legislation in domains such as environmental, industrial, or occupational regulation (Acemoglu et al., 2026)? Which types of firms are first to create new roles—smaller start-ups or larger firms closer to the technological frontier—and does this depend on the type of new work?

4. Conceptually, our analysis suggests that canonical task models should incorporate labor supply dynamics. Current models ensure new task emergence raises labor share solely by increasing the proportion of tasks performed by labor. However, our evidence indicates that the impact of new work operates through an additional channel: creating demand for scarce expertise that generates quasi-rents for workers who acquire new skills. This mechanism provides a more complete account of how new work offsets automation's effects and can help explain to whom the benefits of new work may accrue.

This expertise-based perspective has broader implications for understanding labor market dynamics. As the skills required for new work diffuse and premiums erode, sustaining new work's role in reinstating labor's share requires continual innovation and skill formation. This suggests that economies capable of generating successive waves of expertise-demanding new work—and equipping workers with the required skills—may be better positioned to maintain labor's income share in an era of advancing automation.

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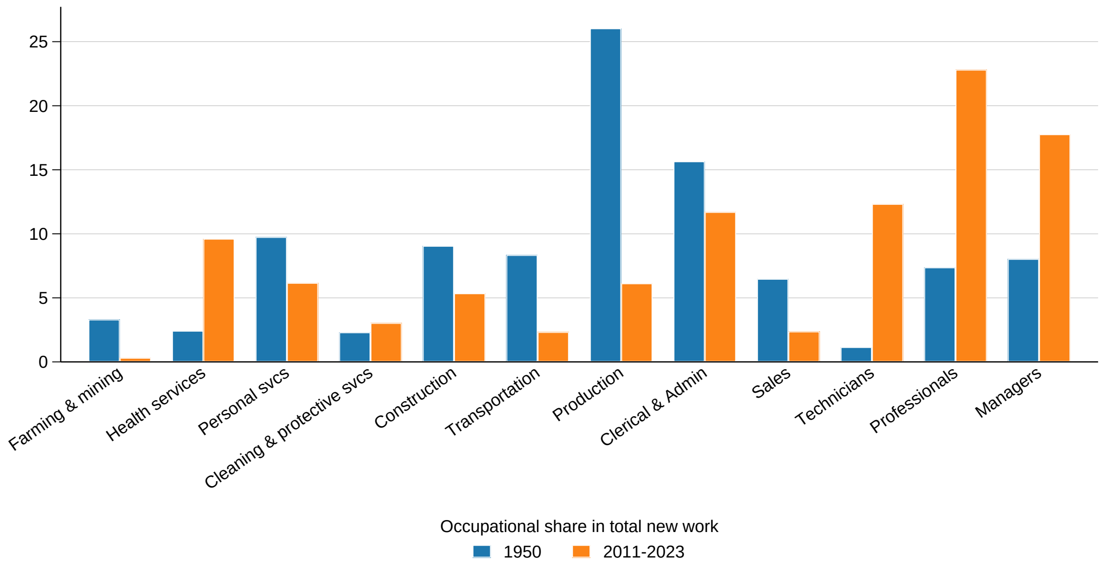
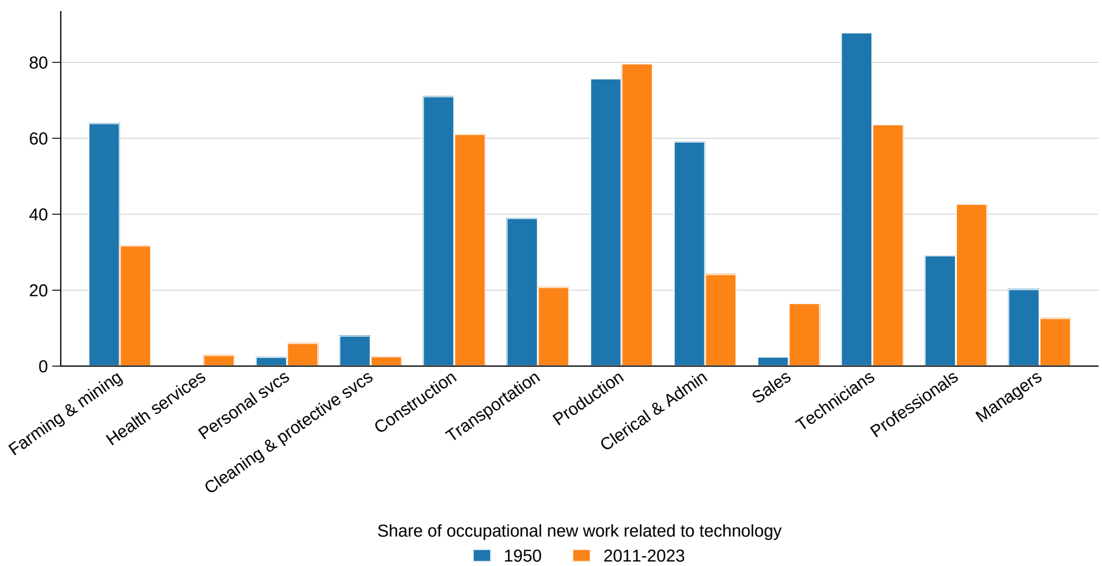
Figures

Figure 1: Distribution of New Work by Broad Occupation

A. Between occupation share of new work, by time period

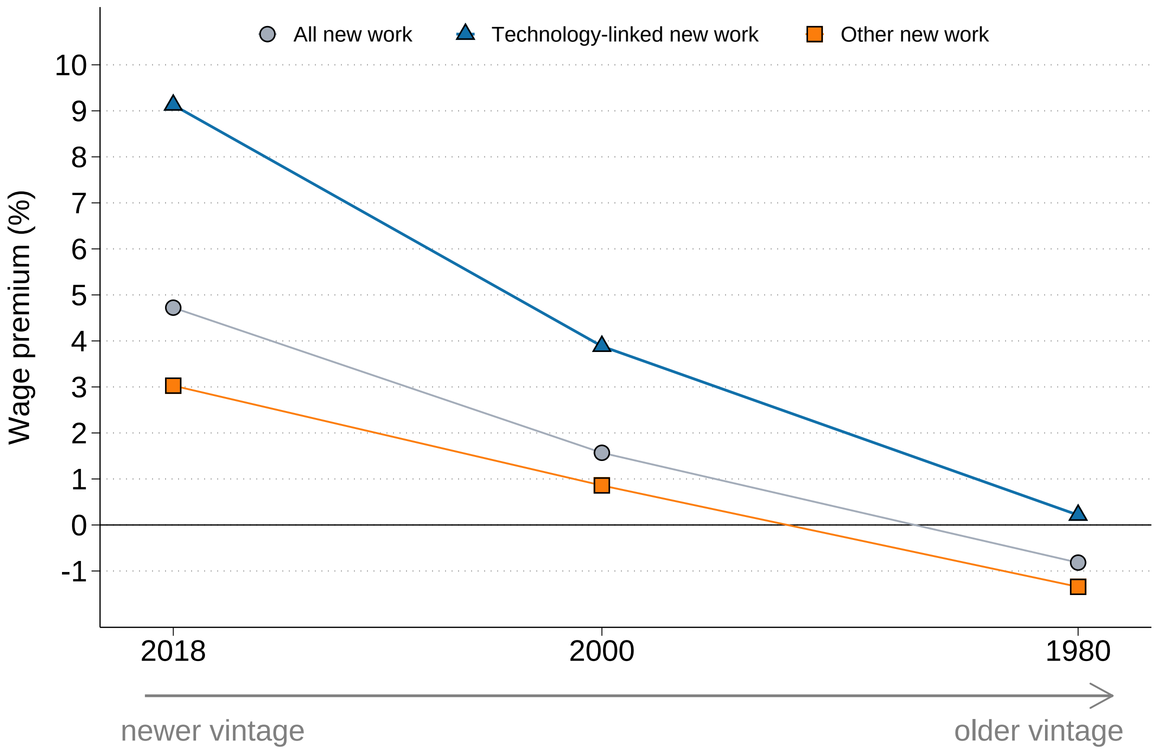


B. Within occupation share of technology-linked new work, by time period



Notes: Occupations are ordered from lowest to highest paying. In each panel, the first set of bars correspond to new work emerging between 1930 and 1950, measured using the 1950 CCC. The second set of bars correspond to new work emerging from 1970 to 2018, measured in the ACS over 2011 and 2014–2023. Panel A shows the share of total employment in new work commanded by each occupation group, separately by time period. For instance, the farthest left bar shows that employment in new work in "Farming and Mining" occupations comprised 3.3% of total employment in new work in 1950. Panel B shows the share of employment in new work within a given occupation group which is categorized as technology-related. Here, the farthest left bar shows that 64% of employment in new work among "Farming and Mining" occupations in 1950 was technology-related. A tabular version of these data is available in Appendix Table A1.

Figure 2: New Work Wage Premium by Vintage, 2011–2023



Notes: Figure reports wage premium estimates from equation (1), augmented with new work vintage dummies. The regression specification includes controls for survey year, demographics, self-employment and urban/rural status, and contains fixed effects for industry, occupation, and county. The 1980 vintage includes titles introduced between 1970 and 1980; the 2000 vintage includes titles introduced between 1980 and 2000; and the 2018 vintage includes titles introduced between 2000 and 2018. Standard errors are omitted from the figure as estimates are very precise. Corresponding regression coefficients and standard errors are available in column 4 of Appendix Tables A3 and A4.

Tables

Table 1: Who is Employed in New Work? Linear Probability Estimates
Dependent variable: Dummy for employment in new work (× 100)

	2011–2023			1950		
	(1)	(2)	(3)	(4)	(5)	(6)
Less than high school	-2.54***	-0.51***	-0.51***	-0.82***	-0.57***	-0.37***
	(0.00)	(0.00)	(0.00)	(0.03)	(0.03)	(0.03)
Some college	4.08***	1.36***	1.18***	0.23***	0.64***	0.47***
	(0.00)	(0.00)	(0.00)	(0.05)	(0.05)	(0.05)
BA or above				1.43***	1.46***	1.26***
				(0.05)	(0.06)	(0.06)
BA	5.22***	1.80***	1.58***			
	(0.00)	(0.00)	(0.00)			
More than BA	4.85***	3.27***	2.91***			
	(0.00)	(0.00)	(0.00)			
Ages 30–54	1.29***	-0.34***	-0.36***	-0.05*	0.13***	0.04+
	(0.00)	(0.00)	(0.00)	(0.02)	(0.02)	(0.02)
Ages 55–64	0.25***	-0.76***	-0.79***	-1.02***	-0.27***	-0.34***
	(0.00)	(0.00)	(0.00)	(0.04)	(0.03)	(0.03)
Female	1.93***	1.36***	1.10***	-0.33***	0.97***	0.95***
	(0.00)	(0.00)	(0.00)	(0.02)	(0.03)	(0.03)
Asian	4.31***	-0.05***	-0.46***	-1.34***	-0.39+	-0.97***
	(0.01)	(0.00)	(0.00)	(0.25)	(0.23)	(0.23)
Black	-0.34***	-0.93***	-0.73***	-2.74***	-1.08***	-1.30***
	(0.00)	(0.00)	(0.00)	(0.03)	(0.03)	(0.04)
Hispanic	-2.00***	-1.18***	-0.37***	-1.15***	-0.56***	-0.95***
	(0.00)	(0.00)	(0.00)	(0.09)	(0.08)	(0.09)
Self-employed	-4.52***	-3.41***	-2.95***	-2.33***	-1.60***	-1.37***
	(0.01)	(0.01)	(0.01)	(0.03)	(0.04)	(0.04)
Urban	1.32***	0.71***	0.44***	1.47***	0.49***	0.25***
	(0.00)	(0.00)	(0.00)	(0.02)	(0.02)	(0.03)
Year	X	X	X	X	X	X
Occupation		X	X		X	X
Industry			X			X
County			X			X
R^2	0.009	0.217	0.224	0.004	0.116	0.123
N		18,360,000			6,117,001	
Dep. var. mean		18.31			7.24	

Notes: Reference group: high school, age ≤ 30, male, white, not self-employed, rural. Columns (1)–(3) report linear probability estimates of employment in work introduced since 1970 using the 2011 and 2014–2023 ACS. Columns (4)–(6) report analogous estimates of work introduced between 1930–1950 using the 1950 CCC. Coefficients multiplied by 100. Robust standard errors in parentheses. $+ < 0.1$, $* < 0.05$, $** < 0.01$, $*** < 0.001$.

Table 2: Wages in New Work: Contemporary and Historical Evidence
Dependent variable: Log wage × 100

	A. All new work			
	(1)	(2)	(3)	(4)
	A1. 2011–2023			
New work	15.58***	2.65***	2.46***	1.81***
	(0.01)	(0.01)	(0.01)	(0.01)
R^2	0.019	0.336	0.469	0.499
N	18,360,000			
	A2. 1950			
New work	9.00***	2.80***	2.40***	1.42***
	(0.10)	(0.11)	(0.10)	(0.10)
R^2	0.001	0.159	0.213	0.236
N	6,117,001			
	B. New work by type: Technology-linked vs. other			
	(1)	(2)	(3)	(4)
	B1. 2011–2023			
Technology-linked new work	45.08***	8.28***	5.78***	3.79***
	(0.01)	(0.01)	(0.01)	(0.01)
Other new work	1.34***	0.34***	1.09***	1.00***
	(0.01)	(0.01)	(0.01)	(0.01)
R^2	0.025	0.337	0.469	0.499
N	18,360,000			
	B2. 1950			
Technology-linked new work	17.16***	6.13***	3.73***	2.20***
	(0.13)	(0.13)	(0.13)	(0.13)
Other new work	1.88***	-0.53**	1.06***	0.64***
	(0.15)	(0.16)	(0.16)	(0.15)
R^2	0.002	0.159	0.213	0.236
N	6,117,001			
Year	X	X	X	X
Occupation		X	X	X
Demographics			X	X
Industry				X
County				X

Notes: Table reports wage premium estimates by new work type. Panel A reports estimates for employment in all new work. Panel B reports estimates separately for technology-linked and other new work. Panels A1 and B1 use the 2011 and 2014–2023 ACS and define new work as occupation titles first introduced since 1970. Panels A2 and B2 report analogous estimates using the 1950 CCC and define new work as titles introduced between 1930 and 1950. Demographic controls include age, age^2, sex, self-employment status, urban/rural status, and fixed effects for level of education and race. These coefficients are suppressed for brevity. Table coefficients multiplied by 100. Robust standard errors in parentheses. $+ < 0.1, * < 0.05$, $** < 0.01, *** < 0.001$.

Table 3: New Work Transition Rates, 1940–1950 Linked Worker Sample

	A. Employment shares in new work (%)	
	1940	1950
New work employment share	2.24	7.47
	B. Transition probabilities (%)	
	Preexisting work 1950	New work 1950
Preexisting work 1940	92.79	7.21
New work 1940	81.02	18.98

Notes: N = 1,826,167. Transition probabilities are conditional on employment in both periods. Employment in new work in 1940 includes the 1940 new work vintage. Employment in new work in 1950 includes both 1940 and 1950 new work vintages.

Table 4: Wages in New Work, 1940–1950 Linked Worker Sample
Dependent variable: 1950 Log wage (× 100)

	(1)	(2)	(3)	(4)	(5)
New work in 1950	5.08***	5.05***	3.79***	3.60***	3.41***
	(0.18)	(0.18)	(0.17)	(0.17)	(0.17)
New work in 1940		2.35***	1.15***	0.99**	0.66+
		(0.35)	(0.35)	(0.35)	(0.34)
Occupation	X	X	X	X	X
Demographics			X	X	X
Industry				X	X
County				X	X
1940 Log wage					X
R^2	0.066	0.066	0.106	0.112	0.122
N			1,826,167		

Notes: Conditional on employment in both periods. Employment in new work in 1940 includes the 1940 new work vintage. Employment in new work in 1950 includes both 1940 and 1950 new work vintages. Demographic controls include age, age^2, sex, self-employment status, urban/rural status, and fixed effects for level of education and race. Coefficients multiplied by 100. Robust standard errors in parentheses. + <0.1, * <0.05, ** <0.01, *** <0.001.

Table 5: Effects of a Positive Demand Shock on New Work Emergence

	Employment growth	New work employment share (%)		Tech-linked new work employment share (%)	
	1940–1950	1940	1950	1940	1950
	(1)	(2)	(3)	(4)	(5)
			A. All employment		
Treated counties	0.10***	0.03	0.35**	0.05+	0.30***
	(0.02)	(0.05)	(0.11)	(0.03)	(0.09)
County-level controls	X	X	X	X	X
R^2	0.389	0.339	0.632	0.263	0.504
N			1,403		
			B. Manufacturing industry employment		
Treated counties	0.16***	0.15	0.61***	0.08	0.55***
	(0.05)	(0.10)	(0.17)	(0.07)	(0.16)
County-level controls	X	X	X	X	X
R^2	0.263	0.066	0.172	0.130	0.130
N			1,403		

Notes: Coefficients in columns (2)–(5) multiplied by 100. Control variables are the most complete set of county-level controls from Garin and Rothbaum (2025). Employment in new work in 1940 includes the 1940 new work vintage. Employment in new work in 1950 includes both 1940 and 1950 new work vintages. Standard errors clustered by county in parentheses. + <0.1, * <0.05, ** <0.01, *** <0.001.

Table 6: Worker Transitions into New Work Following a Demand Shock, 1940–1950
Dependent variable: Dummy for employment in new work in 1950 (× 100)

	(1)	(2)	(3)	(4)	(5)
Employed in treated county in 1940	1.45***	1.40***	0.41***	0.40***	0.40***
	(0.13)	(0.13)	(0.10)	(0.10)	(0.10)
Employed in new work in 1940		X	X	X	X
Occupation in 1940			X	X	X
Demographics				X	X
Industry in 1940					X
R^2	0.001	0.004	0.023	0.024	0.024
N			4,047,840		
Dependent variable mean			5.67		

Notes: Conditional on employment in both periods. Observations include workers linked across 1940 and 1950 CCC surveys. Demographic controls include age, age^2, sex, self-employment status, urban/rural status, and fixed effects for level of education and race. Coefficients multiplied by 100. Standard errors clustered by county in parentheses. $+ < 0.1, * < 0.05$, $** < 0.01, *** < 0.001$.

Appendix

Table of Contents

A Data and methods

A.1 Sample construction

A.1.1 American Community Survey

To construct contemporary measures of new work, we use individual-level microdata from the American Community Surveys (ACS) from 2011 and 2014 through 2023. We exclude the 2012 and 2013 surveys as they lack fields required for our analyses: 2012 lacks person weights, and 2013 lacks occupational write-ins. We restrict the sample to employed respondents, aged 16 to 64 with positive earnings and non-missing occupation codes. We further exclude unpaid family workers and those in military occupations. Applying these restrictions retains 41% of all ACS respondents. Finally, as our new-work classification relies on the occupational write-in field, *ocw1*, we drop records with missing write-ins. The final sample size is approximately 18,360,000 individuals and represents about 35% of the full set of ACS respondents.

A.1.2 Census Complete Count

We use 1940 and 1950 Census Complete Count data (Ruggles et al., 2024)[19], retaining respondents who meet our employment definition of being aged 16 to 64, having a job (excluding unpaid family workers) with positive annual earnings, having non-missing occupation and industry codes, and not living in a group quarter. We additionally extract workers' gender, age, race, education, self-employment status, urban status, and county of residence. In 1950, earnings and education are only available for sample line observations, which make up 20% of the 1950 dataset: each of these observations is therefore assigned a weight of 5 in our analyses, although we report unweighted observation numbers.

The current 1950 Census Complete Count release contains mismeasured earnings data, with correct values in roughly 70–75% of cases[20]. Specifically, multiple values were written in the allotted space on the census forms, leading to erroneous data capture. While this was adjusted using targeted truncation, the documentation notes that wages are underestimated twice as frequently as they are overestimated. We therefore trim the bottom 10% of earnings within each Census occupation in the 1950 data. Further, educational attainment is underestimated in 1950 due to other data capture issues: there are too many people with one year or less of schooling and too few in the higher grades; and persons who completed high school or attended college are underrepresented by approximately 15%.

We additionally link individuals across these two Census datasets using the MLP crosswalk file made available by IPUMS (Ruggles et al., 2025).[21] This crosswalk matches around 35% of worker observations across years, with male workers having significantly higher match rates than female workers because the algorithm relies on last names.

[19]We use the latest available versions of these datasets, both released in January 2025.
[20]See https://usa.ipums.org/usa/full_count.shtml.
[21]See https://usa.ipums.org/usa/mlp/mlp_crosswalk_guide.shtml.

A.2 Identifying workers employed in new jobs

A.2.1 Identifying new work in the Census Alphabetical Index of Industries and Occupations

Our analysis builds on identification of new occupations using the Census Alphabetical Index of Industries and Occupations (CAIO) from Autor et al. (2024). The detailed methodology for the construction of these data is available in Online Appendix D1 of Autor et al. (2024). For clarity and context we briefly highlight relevant aspects of the data structure.

The CAIO is the Census Bureau's catalog of approximately 35,000 detailed standardized occupational titles each classified to a Census occupation code. This catalog is updated (roughly) every decade to reflect newly emerging occupational titles reported in Census survey responses. Autor et al. (2024) extract these newly added titles for each CAIO edition from 1930 until 2018 by comparing consecutive CAIO editions across decades. This procedure uses a combination of automated matching and manual review, and excludes changes due solely to renaming or formatting. This produces a set of new titles used to measure the emergence of new work over 1930–2018. For instance, the title "Computer applications developer" is categorized as new in the 2000 edition of CAIO, implying that this occupation emerged between 1990 and 2000.

In this paper, we refer to new work emerging over different time periods as "vintages" of new work. For the contemporary analysis based on 2011–2023 ACS data, we use new work lists from the CAIO in 1980, 1990, 2000, and 2018 (i.e. new work emerging from 1970 until 2018). In our analyses, the 1980 "vintage" includes titles introduced between 1970 and 1980; the 2000 "vintage" pools CAIO titles from 1990 and 2000 to represent new work introduced between 1980 and 2000; and the 2018 "vintage" includes titles introduced between 2000 and 2018. We exclude the 2010 CAIO year because its few new title additions are already contained in and marked as new in the 2018 release. The 1990 vintage introduces a smaller set of new titles. We retain these by pooling the 1990 and 2000 vintage matches and refer to the combined set as the 2000 vintage. The differences in quantity of titles in 2010 and 1990 likely reflect administrative priorities within the Census Bureau rather than underlying changes in the prevalence of new work.

For the historical analysis based on 1940 and 1950 CCC data, we use new work vintages of 1940 and 1950 (i.e. new work emerging over 1930–1950).

A.2.2 Matching ACS and Census write-ins to new occupation titles

Respondents to the ACS and Decennial Census surveys in our sample report their occupation as free text. We refer to these transcribed responses as "occupational write-ins". We classify individuals as employed in new work by matching each write-in to a detailed title in the CAIO. If the matched CAIO title is flagged as new, they are coded as employed in new work.

One departure from Autor et al. (2024) concerns our treatment of new titles labeled with "n.s." (not specified) or "n.e.c." (not elsewhere classified). We re-classify any of these titles as preexisting if they were originally marked as new. They typically occur when a title from a prior decade is divided into multiple specific titles and a more generic residual (e.g. "Ironworker" was later split into "Ironworker, construction, roads", "Ironworker, rebar" in 2000, along with a more generic "Ironworker \n.s., other activity or none"). Other examples of generic new work include "Aircraft worker, n.s." which was added in 1990 as a new title to the census occupation category of Machine operators, n.s. (COC 779), "Boat builder, n.s.", which was added in 2000 as a new title to Miscellaneous assemblers and fabricators (COC 775), and "Computer consultant n.e.c. or n.s.", which was added in 2000 to Computer scientists and systems analysts (COC 100). In Autor et al. (2024) new work was measured as the share of CAIO titles in a given Census occupation-year categorized as new, so including these titles as new appropriately reflected the expansion of new work within that occupation. Since respondents do not write "n.s."/"n.e.c." on surveys, we remove these markers from the CAIO, leading to highly generic titles. These generic titles have disproportionately high match rates to occupational write-ins, artificially inflating our estimated level of new work. Our adjustment yields a more conservative measure of new work more appropriate for the person-level matching strategy.

Following this adjustment to new title categorization, we clean the CAIO, ACS, and CCC datasets to improve the accuracy of our matching procedure. The occupational write-ins and CAIO titles are transformed to lower-case, then cleaned and standardized by removing punctuation, extra whitespace, and other extraneous phrases. CAIO titles with common abbreviations are manually corrected to include the full expansion of the abbreviation (for example, C.E.O. is converted to "Chief Executive Officer"). Next, we trim any text following the appearance of "exc." from the CAIO titles. For example, "Chief deputy, exc. police and sheriff" is transformed to "Chief deputy". The cleaned text is then spell-corrected to reduce transcription or reporting errors. We use Python's SpellChecker package to correct for misspellings, augmenting the default dictionary with CAIO titles so similar write-ins resolve to valid occupational titles.

With the CAIO and write-in data cleaned, we proceed to matching. We match write-ins to CAIO titles within the same occupation code. The Census Bureau updates their occupation codes over time, so we utilize stable occupation code definitions from Autor et al. (2024) and restrict our matches to be within these stable occupation codes. In the historical sample, the CCC write-ins and CAIO titles are merged using a set of 166 occupation codes that are consistent between the 1940 and 1950 Census surveys. In the contemporary sample, the ACS write-ins are merged using 306 occupation codes that are stable across the 1980–2018 Census surveys.[22]

In the historical analysis, we link occupational write-ins to CAIO titles using a word embeddings approach. We encode cleaned CAIO and CCC strings using a sentence transformers model to construct a vector representation of occupation text, where semantically similar occupations lie closer in this space. The model, `sentence-transformers/all-mpnet-base-v2`, is an adaptation of the widely used BERT model that is optimized to encode multi-word text. Within each consistent occupation, we calculate pairwise cosine similarity scores between

[22] In the ACS contemporary data, we utilize occ1990dd_18, which is an adaptation of David Dorn's occ1990dd (Autor and Dorn, 2013). For the historical CCC we utilize occ1950rj. The details of these occupation code construction and relevant crosswalks are available in the Online Appendix of Autor et al. (2024).

each respondent's write-in and the CAIO occupation titles belonging to that occupation. Respondent write-ins are assigned to the CAIO title with the highest similarity score. As we expect new work to be less common than employment in existing work, we introduce an additional conservative measure to our matching process. Matches to "new work" with similarity scores below 0.7 are re-classified as existing work to reduce false positives. Write-ins from the CCC are linked to CAIO titles from 1940 and 1950 vintages, and are categorized as new if at least one matched title is new.

We perform a similar exercise in our contemporary data. Due to the restricted nature of the Census computing environment, we use fuzzy matching rather than word embeddings to establish the match. Specifically, we utilize Scikit-Learn's TFIDFVectorizer function and perform a 3-character ngram fuzzy match to generate a cosine similarity score ranging from 0 to 1.[23] To parallel our methodology in the historical sample, we assign each ACS write-in response to the highest scoring matched CAIO title within the same consistent occupation code. In the contemporary setting, we re-categorize write-ins matched to new work with match scores below 0.5 to preexisting work.[24] Write-ins from the ACS are linked to CAIO titles from 1980, 1990, 2000, and 2018 vintages, and are categorized as new if at least one matched title is new.

Finally, to perform our vintage analysis (presented in Figure 2), each respondent who is classified as employed in new work is assigned a unique vintage-match. To do this, we assign each respondent to the vintage associated with the highest scoring new-title match. Ties are broken in favor of the most recent vintage. In our ACS data, this results in 5.96% of respondents among our sample being categorized as in new work emerging in some vintage since 1970. In the historical sample, 7.23% of respondents are employed in new work since 1930.

A.2.3 Classifying new occupation titles as technology-linked or not

To classify new titles as technology-related, we use the following prompt, which we send to the GPT4o model API (specifically, we use the OpenAI Python API to query the "gpt-4o-2024-11-20" model):

```
You are an economist and are an expert on labor markets. You have a theory that posits that new
work performed by humans can be driven either by technological change which affects the nature of
tasks performed, or by shifting demands for more specific types of services. You are analyzing
the proliferation of new specific occupational titles that are categorized under the broader
umbrella of existing Census occupation codes. The introduction of distinct new titles within
Census occupation codes over time are considered to be "new work" within that occupation.
```

The new title "<occ_title>" was introduced in the United States between <year minus 10*> and <year> to the Census occupation entitled "<occ_code_label>". Do you expect this title to be related to technology-driven new work, service-driven new work, or neither/uncertain? Along with your answer, provide a brief explanation. Follow the coding scheme "0" for

[23] As a sensitivity check, we also experimented with utilizing a 1-word ngram TF-IDF match. Our results in the ACS-based analyses were quantitatively similar when using this alternative match methodology, but we found the fuzzy match to be more consistent and accurate.

[24] Our findings are robust to varying this matching score cut-off.

service-driven new work, “1” for technology driven, and “.” for neither/uncertain. Your response should be formatted in a tuple (category, brief explanation). The final output should only contain this response and nothing else.

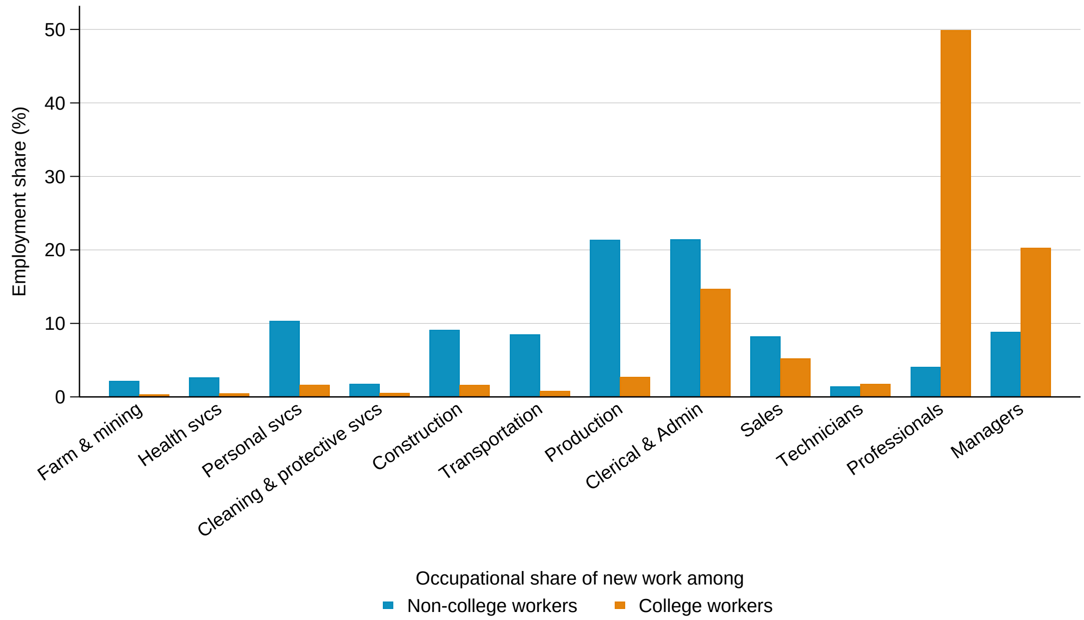
We set the “temperature” parameter on the prompt to zero to minimize any variability in model responses to the prompt. The asterisk in “<year minus 10*>” in the prompt indicates that we replace 2008 with the year 2000 when querying about new titles in 2018, following the convention in Autor et al. (2024). After some inspection of the LLM model output, we classify ambiguous cases as non-technological. Out of 28,007 new occupation titles for which we can obtain LLM labels, GPT4o classifies 15,419 (55%) as technology-related.

As a sanity check, we independently manually classify 100 randomly chosen GPT4o labels, finding 95% human agreement with the large language model classifications. We also verify that technology-linked new titles relate positively with augmentation patent counts from Autor et al. (2024) at the Census occupation level. Specifically, we regress either the share of new titles that are technology-linked or an indicator for having any technology-linked new titles on the (log) count of Autor et al. (2024) augmentation patent linked to year-specific Census occupation codes from 1940 to 2018, and we weight observations by the occupational yearly employment share. Net of year fixed effects, we find highly statistically significant positive correlations of 0.29 and 0.35, respectively.

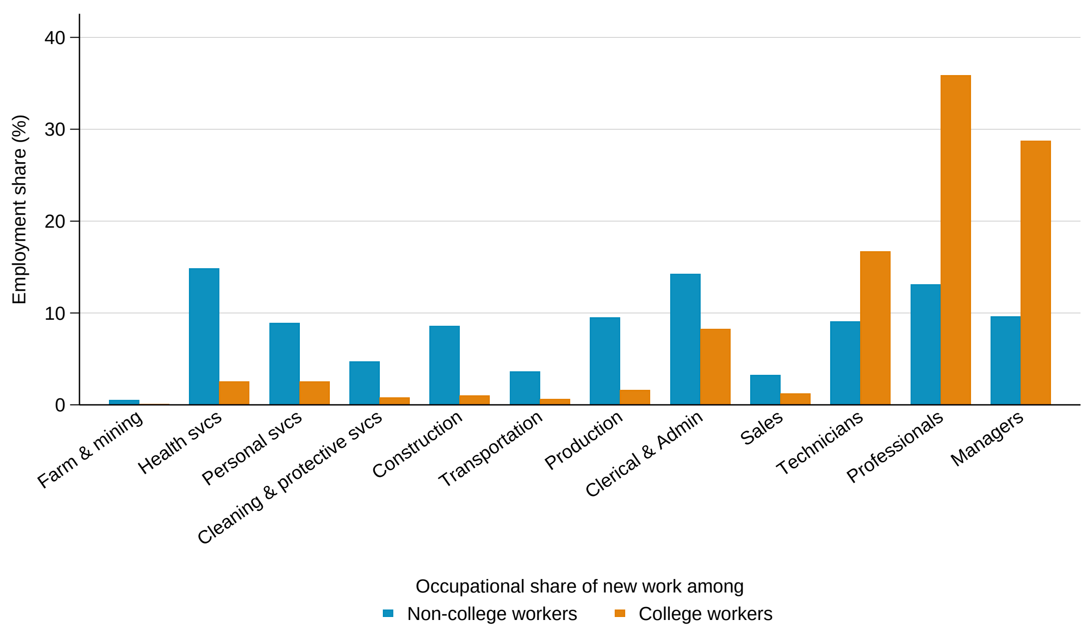
B Appendix Figures

Figure A1: Occupational Distribution of New Work Employment by Broad Educational Group, 1940—1950 and 2011–2023: Non-College Workers vs. College or More

A. 1940–1950



B. 2011–2023



Notes: Figure plots the share of total employment in new work across occupation groups, ordered from lowest to highest paying. Panel A reports shares separately by education level using the 1940 and 1950 CCC matched to CAIO vintages from 1940 and 1950. New work is defined as occupation titles introduced between 1930 and 1950. Panel B reports analogous shares using the ACS from years 2011 and 2014–2023 matched to CAIO vintages from 1980–2018. New work is defined as occupation titles first introduced since 1970. Within each occupation group, the first bar contains estimates from workers with less than four years of college education. The second bar contains estimates from workers with at least four years of college education.

C Appendix Tables

Table A1: Employment Shares and New Work by Occupation Group

Occupation group	A. 2011–2023					B. 1950				
	Emp. share (%)	All new work (%)	Tech new work (%)	Share of all new work (%)	Share of tech new work (%)	Emp. share (%)	All new work (%)	Tech new work (%)	Share of all new work (%)	Share of tech new work (%)
Managers	15.56	20.92	2.65	17.78	6.90	7.21	8.06	1.63	8.04	3.53
Professionals	22.81	18.32	7.82	22.82	29.93	6.44	8.28	2.41	7.38	4.66
Technicians	5.74	39.37	25.07	12.33	24.12	1.66	5.06	4.45	1.16	2.21
Sales	5.99	7.27	1.20	2.38	1.21	7.05	6.65	0.16	6.49	0.35
Clerical & Admin	13.89	15.43	3.73	11.70	8.70	15.12	7.49	4.43	15.66	20.05
Production	7.59	14.80	11.79	6.13	15.01	28.35	6.64	5.03	26.05	42.71
Transportation	5.92	7.23	1.51	2.34	1.49	6.30	9.58	3.73	8.35	7.05
Construction	6.14	15.99	9.77	5.36	10.06	9.45	6.93	4.92	9.06	13.94
Cleaning & Prot.	4.22	13.19	0.34	3.04	0.24	3.17	5.26	0.42	2.31	0.40
Personal Services	7.98	14.17	0.86	6.17	1.15	6.77	10.41	0.25	9.75	0.51
Health Services	3.28	53.67	1.57	9.62	0.86	0.44	40.11	0.00	2.44	0.00
Farming & Mining	0.90	6.58	2.09	0.32	0.32	8.03	2.98	1.91	3.31	4.59
Weighted mean		18.31	5.96				7.23	3.34		
N			18,360,000					6,564,827		

Notes: Panel A reports employment and new work shares calculated using the ACS from 2011 and 2014–2023. New work is defined as titles introduced since 1970. Panel B reports employment and new work shares using the 1950 CCC. New work is defined as titles introduced between 1930–1950. In each panel, the first column reports the occupation's share of total employment (sums to 100). The second column reports the share of workers within each occupation employed in new work. The third column reports the share of workers within each occupation employed in tech-linked new work. The fourth column reports the share of total new work contained in each occupation. The fifth column reports the share of total tech-linked new work contained in each occupation.

Table A2: Imputed and Direct Estimates of New Work Since 1970

Occupation group	New title share (%)	New work share direct (%)	Share of all new work imputed (%)	Share of all new work direct (%)
Managers	29.78	20.92	15.21	17.78
Professionals	33.00	18.32	22.97	22.82
Technicians	38.59	39.37	6.78	12.33
Sales	44.92	7.27	6.95	2.38
Clerical & Admin	31.91	15.43	12.37	11.70
Production	29.33	14.80	7.00	6.13
Transportation	25.05	7.23	5.07	2.34
Construction	38.85	15.99	8.36	5.36
Cleaning & Prot	23.87	13.19	3.07	3.04
Personal Services	35.98	14.17	7.48	6.17
Health Services	42.95	53.67	3.82	9.62
Farming & Mining	23.85	6.58	0.92	0.32
Weighted mean	32.84	18.31		

Notes: Table reports imputed estimates of new work based on new CAIO title shares, and direct estimates of new work using the ACS from 2011, and 2014–2023. New work is defined as CAIO occupation titles first introduced since 1970. Col (1): Share of new CAIO titles within each occupation group categorized as new. Col (2): Within-occupation group new work employment share calculated as the fraction of ACS respondents within each occupation group matched to new CAIO titles. Also reported in column (2) of Table A1. Col (3): Imputed share of total new work contained in each occupation group. Estimated by multiplying each occupation group's new-title share from column (1) by its share of total employment, then dividing the resulting group-specific imputed new-work amount by aggregate imputed new work. Col (4): Share of total employment in new work contained in each occupation group. Calculated as the fraction of all respondents matched to new CAIO titles who are employed in each occupation group. Also reported in column (4) of Table A1.

Table A3: Wages in New Work by Vintage of Emergence
Dependent variable: 2011–2023 Log wage (× 100)

	(1)	(2)	(3)	(4)
New in 2018 vintage	14.10***	7.70***	6.81***	4.72***
	(0.01)	(0.01)	(0.01)	(0.01)
New in 2000 vintage	15.14***	0.58***	1.21***	1.57***
	(0.01)	(0.01)	(0.01)	(0.01)
New in 1980 vintage	17.95***	0.84***	-0.01	-0.82***
	(0.01)	(0.01)	(0.01)	(0.01)
Year	X	X	X	X
Occupation		X	X	X
Demographics			X	X
Industry				X
County				X
R^2	0.019	0.337	0.469	0.499
N	18,360,000			

Notes: New work wage premium estimated using the ACS from 2011 and 2014–2023 linked to CAIO vintages in 2018, 2000, and 1980. Omitted group contains individuals employed in work that existed before 1970. Demographic controls include age, age^2, sex, self-employment status, urban/rural status, and fixed effects for level of education and race. Coefficients multiplied by 100. Robust standard errors in parentheses. + <0.1 * <0.05, ** <0.01, *** <0.001.

Table A4: Wages in New Work by Vintage and Type
Dependent variable: 2011–2023 Log wage (× 100)

	(1)	(2)	(3)	(4)
Technology-linked new work				
2018 vintage	69.65***	15.91***	12.10***	9.13***
	(0.02)	(0.02)	(0.02)	(0.02)
2000 vintage	50.60***	9.00***	5.87***	3.89***
	(0.02)	(0.02)	(0.02)	(0.01)
1980 vintage	20.54***	2.65***	1.57***	0.22***
	(0.02)	(0.02)	(0.02)	(0.02)
Other new work				
2018 vintage	-10.37***	4.70***	4.86***	3.03***
	(0.02)	(0.01)	(0.01)	(0.01)
2000 vintage	1.78***	-2.24***	-0.32***	0.86***
	(0.01)	(0.01)	(0.01)	(0.01)
1980 vintage	15.94***	0.19***	-0.79***	-1.34***
	(0.02)	(0.02)	(0.02)	(0.01)
Year	X	X	X	X
Occupation		X	X	X
Demographics			X	X
Industry				X
County				X
N	18,360,000			
R^2	0.028	0.337	0.469	0.499

Notes: New work wage premium by type of new work estimated using the ACS from 2011, and 2014–2023. New work is defined as occupation titles first introduced since 1970. Omitted group contains individuals employed in work that existed before 1970. Demographic controls include age, age^2, sex, self-employment status, urban/rural status, and fixed effects for education and race. Coefficients multiplied by 100. Robust standard errors in parentheses. + <0.1 * <0.05, ** <0.01, *** <0.001.

Table A5: Persistence of Employment in New Work, 1940–1950 Linked Worker Sample
Dependent variable: 1950 Employment in new work

	(1)	(2)	(3)	(4)
	A. 1940 & 1950 new work vintages			
New work in 1940	11.77***	6.28***	6.22***	6.08***
	(0.20)	(0.19)	(0.19)	(0.19)
R^2	0.004	0.017	0.019	0.020
N	1,826,167			
Dependent variable mean	7.47			
	B. 1950 new work vintage only			
New work in 1940	5.76***	1.47***	1.42***	1.34***
	(0.16)	(0.14)	(0.14)	(0.14)
R^2	0.001	0.017	0.018	0.019
N	1,826,167			
Dependent variable mean	4.85			
Occupation in 1940		X	X	X
Demographics			X	X
Industry in 1940				X
County in 1940				X

Notes: Conditional on employment in both periods. Persistence of employment in new work estimated using the 1950 CCC matched to 1940 and 1950 CAIO titles in Panel A and 1950 CAIO titles in Panel B. Observations include workers linked across 1940 and 1950 CCC surveys. Demographic controls include age, age^2, sex, self-employment status, urban/rural status, and fixed effects for level of education and race. Coefficients multiplied by 100. Robust standard errors in parentheses. + <0.1, * <0.05, ** <0.01, *** <0.001.