New Skills, Higher Pay? Evidence from Job Postings*

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February 2026

Abstract

We study how labor markets price newly emerging skills within jobs. Using more than 53 million U.S. online postings from Lightcast between 2010 and 2024, we identify "new skills" as those rarely requested in 2010–11 but prevalent thereafter. New skill demands—including those that are AI-related—are heavily concentrated in computer and analytical domains across occupations, with little emphasis on routine work. Comparing vacancies within the same detailed occupation, industry, firm, and county in a given year and conditioning on the overall number of listed skills, we find that postings listing at least a new skill offer 2–4 percent higher wages; the premium increases steeply with the number of new skills and is concentrated in IT skills. Notably, new skills related to developing AI tools carry a premium of about 9 percent, compared with about 4 percent for new skills linked to using AI tools. In contrast to new skills, new job titles are a weaker signal of market value: new-title postings do not carry a wage premium by itself but only if paired with new skills. Linking new skills to upstream breakthrough patents yields substantially larger returns—a finding reinforced by instrumental variable estimates—tying wage premia to frontier technological innovation.

Keywords: Job Postings, Skill Demand, Wage Premia, Technological Change, Patents
JEL codes: J21, J23, J24, J31, O33, O34

*We thank Jaden Jonghyuk Kim and Longji Li for excellent research assistance. We thank Manolis Chatzikonstantinou, Gabriela Cugat, Gustavo de Souza, Lukas Freund, Pierre-Olivier Gourinchas, Florence Jaumotte, Philipp Kircher, Giovanni Melina, Marc Muendler, Elias Papaioannou, Antonio Spilimbergo, and numerous seminar participants for insights and comments that have improved this paper. The views expressed in this paper are those of the authors and do not necessarily represent the views of the IMF, its Executive Board, or its management. The authors declare that they have no financial or other ties related to this research project. All errors are our own.

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1 Introduction

Work evolves not only because workers move across occupations and new occupations are created, but also because the content of work changes within occupations as the set of required skills shifts over time.[1] These within-occupation changes can reflect different forces: the adoption of new technologies and tools that reshape production processes, or broader changes in demand, policy, or regulation. Yet skill change is difficult to observe in traditional data sources used to study wage determination. Household surveys and administrative earnings records typically classify workers by occupation and industry but offer limited information on the specific capabilities employers demand within jobs. As a result, a basic question remains surprisingly open: when new skill requirements emerge in jobs, where do they originate, how does the labor market price them, and how do these returns vary across occupations and skill types?

This paper tackles these questions using U.S. vacancy postings from Lightcast from 2010 to 2024, which report both employer-requested skills and posted compensation. The data allow us to observe the evolution of skill demand at high frequency and at a fine level of detail, and to compare wage offers for postings that are similar in occupation, industry, location, and timing but differ in whether they require newly emerging skills.[2] Following Atalay et al. (2020), we define a skill as "new" based on its timing of adoption in the posting distribution: a skill is classified as new if fewer than 1 percent of all postings that ever list the skill between 2010 and 2024 occur in 2010–2011, and the skill's emergence year is the first year in which its prevalence rises above this threshold. Using this definition, we find that roughly one in ten postings requests at least one new skill in 2024, and 7 percent of the more than 33,000 skills in our taxonomy meet the criterion for novelty. We additionally capture AI-related new skill requirements by adapting existing taxonomies from the Stanford AI Index (Maslej et al. 2025) to our set of new skills, distinguishing between "AI Developer" skills that support the development of AI tools and "AI User" skills that relate to using AI-powered applications.

Two stylized facts characterize the content and distribution of new and AI-related skills that we identified. First, these new skills cluster in non-routine analytical and computational

[1] Using task information derived from job advertisements, Atalay et al. (2020) show that from 1950 to 2000, the primary changes in job content took place within occupations, a pattern that Freeman et al. (2020) demonstrate persists after 2000.

[2] Online postings have become a key lens for measuring evolving skill demands (e.g., Deming and Kahn, 2018; Atalay and Sarada, 2020; Braxton and Taska, 2023; Li, 2026) and for analyzing wage setting and market power via posted salaries (e.g., Azar et al., 2020; Hazell et al., 2022; Hazell and Taska, 2025). We bridge these strands by leveraging posted wages to estimate the valuation of new skills within narrowly comparable jobs.

demands, especially in Information Technology and Business and Data Analysis domains, and AI-related requirements are even more concentrated in these areas.[3] Second, high-skill managerial and professional occupations show the highest intensity of these IT-driven computational requirements, while lower-skill and elementary jobs increasingly integrate Social and Administrative skills and interpersonal skills.

To quantify the economic value of these new skill requirements, we construct a regression sample of over 53 million U.S. online job postings from 2020 to 2024 that report salary information and include non-missing skill requirements, industry, occupation, and firm identifiers.[4] Our empirical strategy leverages the granularity of postings to estimate wage differences within narrowly comparable jobs. The baseline specification compares postings within the same detailed occupation, industry, and county in a given year (and flexibly accounts for salary reporting by interacting pay-period categories with year), while conditioning on the total number of listed skills so that the new skill coefficient is not mechanically capturing the general intensity of requirements. This approach ensures that our estimates are unconfounded by concurrent demand shocks—such as automation trends or routine-biased technical change affecting specific sectors—as well as local demographic shifts in the supply of skills. In our preferred specification, postings that request any new skill offer wages that are about 4.4 percent higher than otherwise comparable postings, and this premium remains 2.3 percent even when we include very saturated fixed effects interacting occupation, industry, county, and year. The premium rises steeply with the number of new skills: in the baseline design, postings listing four or more new skills pay about 10 percent more than postings listing none.

The market does not attach a uniform value to novelty; instead, returns to new skills differ sharply across occupations and skill domains. Across major occupational groups, the new-skill premium is largest in managerial and professional occupations, at around 6 percent, and smallest in clerical support and elementary occupations, at around 2 percent. Across skill domains, analytical and computational skills command the largest wage premia, especially in Information Technology and Business and Data Analysis. By contrast, some domains of new skills are associated with negligible or even negative wage differentials. This heterogeneity is consistent with the view that while some new skills reflect productivity-

[3]The classification is built on two separate foundations: (i) the standardized Lightcast Open Skills taxonomy, which organizes skills into major occupational domains (for example, "Information Technology" or "Business and Data Analysis"); and (ii) Routine versus Non-Routine (RNR) groupings, based on frameworks developed in the task-based research literature.

[4]Recent work by Hazell and Taska (2025) and Hazell et al. (2022) support the use of posted wages for labor market analysis, showing that Lightcast wage data closely tracks administrative benchmarks and reflects actual firm wage-setting.

enhancing complements, others signal task standardization or automation (Acemoglu and Restrepo, 2022; Autor and Thompson, 2025). The same contrast appears within AI: postings requesting AI-developer skill carry wage premia exceeding 9 percent, compared to just 4 percent for AI-user skills, indicating that the economic gains from AI appear to be concentrated in scarce, production-side expertise rather than broad tool adoption.

We next examine the relative importance of new skill content versus new job titles in determining the wage premium for new work. When analyzing these two dimensions jointly, we find that the direct wage return to a new job title is effectively zero (–0.3 percent), while the premium for listing new skills remains robust and economically significant at 2.2 percent. However, we observe a meaningful complementarity: vacancies that combine a new title with new skill requirements command a total premium of approximately 3.6 percent. This pattern suggests that the labor market does not reward novelty in naming per se. Instead, new job titles help employers signal and price the new skills that define the job.

To establish the validity of our findings, we subject our estimates to a battery of robustness checks regarding measurement, inference, and sample composition. We confirm that the estimated wage premium is very robust to alternative definitions of new skills, including varying frequency thresholds (0.5 percent and 2 percent) or using time-rolling emergence criteria. The results also remain statistically significant under multi-way clustering of standard errors and are robust to restricting the sample (1) by excluding staffing intermediaries or (2) to those postings reporting precise point wages. Across all specifications, the positive valuation of new skills remains quantitatively and qualitatively similar.

Finally, we connect the wage valuation of new skills to upstream technological change by linking the skills requested in postings to measures of breakthrough innovation drawn from the patent record. This linkage builds on a growing literature that uses patent text and related innovation measures to track the emergence and diffusion of new technologies in labor markets (e.g., Kalyani et al., 2025; Autor et al., 2024). Empirically, we find that the new-skill premium is markedly larger for skills that are explicitly connected to breakthrough patents, and rises monotonically with the intensity of that linkage. We then exploit this structure in an instrumental variables framework, using pre-determined breakthrough patent exposure as a source of plausibly exogenous variation in demand for new skills. The resulting estimates imply substantially larger wage gains for technology-driven new skills than suggested in the baseline. This result is consistent with the view that frontier innovation disproportionately rewards the capabilities most tightly connected to it.

The remainder of the paper proceeds as follows. Section 2 reviews the related literature and positions our contribution within work on technological change, task content, and skill demand. Section 3 describes the job-posting data, the construction of our skill measures, and the definition of new skills and job titles. Section 4 presents the empirical framework and baseline estimates of the wage premium to new skills. It also examines heterogeneity across occupations and skill domains, including AI-related capabilities, compares skill-based and title-based measures of novelty, and reports a wide range of robustness checks. Section 5 links new skills to breakthrough innovation using patent data and presents instrumental-variable estimates. Section 6 concludes.

2 Related literature

This paper relates to the growing literature that uses job advertisements to measure how work evolves. A prominent strand emphasizes the creation of "new work," captured by the emergence of new job titles and job categories. Using historical job-ad text, Atalay et al. (2020) and Kim et al. (2024) document that large changes in job content occur within occupations. Autor et al. (2024) provide a complementary long-run perspective, tracing the origins and content of newly emerging job categories (new work) over 1940–2018 and highlighting the role of new work in counterbalancing task-displacing automation. These contributions motivate the view that labor markets adjust not only through reallocation across existing jobs but also through the introduction of new tasks and occupations.

We instead take a skill-based perspective on the evolution of work, establishing the emergence of new skills within jobs as a critical margin of labor market adjustment. We show that wage premia are robustly tied to these new skills, providing granular estimates of how emerging labor demands are priced. We also show that new job titles and new skills are highly complementary, with the largest returns occuring when they are paired.

A second strand of the literature uses vacancy data to measure employer demand for skills and to document within-occupation heterogeneity in skill requirements across firms and labor markets. Deming and Kahn (2018) show that skill demands vary substantially even within narrowly defined occupations and that these demands correlate with pay and firm performance, underscoring that job postings provide a meaningful window into changing skill content. Related evidence on within-occupation upskilling emphasizes that rising requirements can reshape who qualifies for jobs and may generate frictions even without occupational reallocation (Burke et al., 2020).[5] This paper contributes to the literature by

[5]Related work using vacancy postings shows that skill requirements can respond to cyclical slack and

focusing on the novelty of skill requirements—identifying newly emerging skills—and estimating their pricing comparing job postings within tight labor market cells. Furthermore, we trace this value to upstream breakthrough innovations, showing that the new-skill premium is tied to exposure to frontier invention.

Third, this paper is related to an emerging literature that uses posted wages in vacancies to study wage setting and skill premia. Recent research shows that posted wages contain systematic information about firms' wage policies and can be used to study wage-setting behavior across locations and job types (Azar et al. 2020; Hazell et al. 2022; Hazell and Taska 2025).[6] Using vacancy-level wage data, we document how wages adjust when the skill content of work changes within occupations, characterizing the specific new skills that drive positive versus negative premia. Our findings connect naturally with evidence on the value of digital skills, confirming that the returns are driven by digital and analytical domains (Ziegler 2021; Garcia-Lazaro et al. 2025).

Finally, the paper relates to the literature that uses patents to measure the arrival, value, and diffusion of technological change. A long tradition treats patenting and patent citations as observable traces of innovation activity and uses citation-based metrics to proxy for the economic significance of innovations (e.g., Griliches, 1990; Trajtenberg, 1990; Hall et al., 2005). More recent work combines patent-based valuation and modern text methods to identify economically consequential innovations and trace how new technologies diffuse across firms, regions, industries, and occupations (e.g., Kogan et al., 2017; Kelly et al., 2021a; Kalyani et al., 2025; Kogan et al., 2017; Li, 2026). Building on these tools, we document substantial heterogeneity in the returns to new skills by anchoring new skills to upstream invention. By linking job postings to breakthrough patent activity in a pre-period—a connection we formalize using an instrumental variable framework—we demonstrate that wage premia are concentrated in new skills tied to frontier innovation, effectively distinguishing them from shifts that reflect re-labeling, compliance, or task standardization.

may remain elevated into the recovery, consistent with recession-period 'upskilling' within occupations (e.g., Hershbein and Kahn, 2018; Modestino et al., 2020; Braxton and Taska, 2023).

[6]Earlier work noted that wage information in online postings was often missing or reported in broad ranges (e.g. Batra et al., 2023); wage disclosure has increased substantially in recent years, plausibly reflecting the spread of pay-transparency mandates. Appendix Table A8 therefore reports robustness checks restricting to postings with point wages.

3 Data and Measurement of New Skills

Drawing on Lightcast job postings, we develop vacancy-based measures of new skills and new AI-related skills for the period 2010–2024, applying frequency thresholds to identify skills that are initially rare but later become widespread. After outlining these definitions, we present concrete examples along with their mapping to broader skill categories. We describe how demand for these new skills is distributed across the economy, highlighting the concentration of new and AI skills across fields and occupations. Finally, we present key descriptive statistics for the job posting data and evaluate their coverage and measurement adequacy for the subsequent wage analysis.

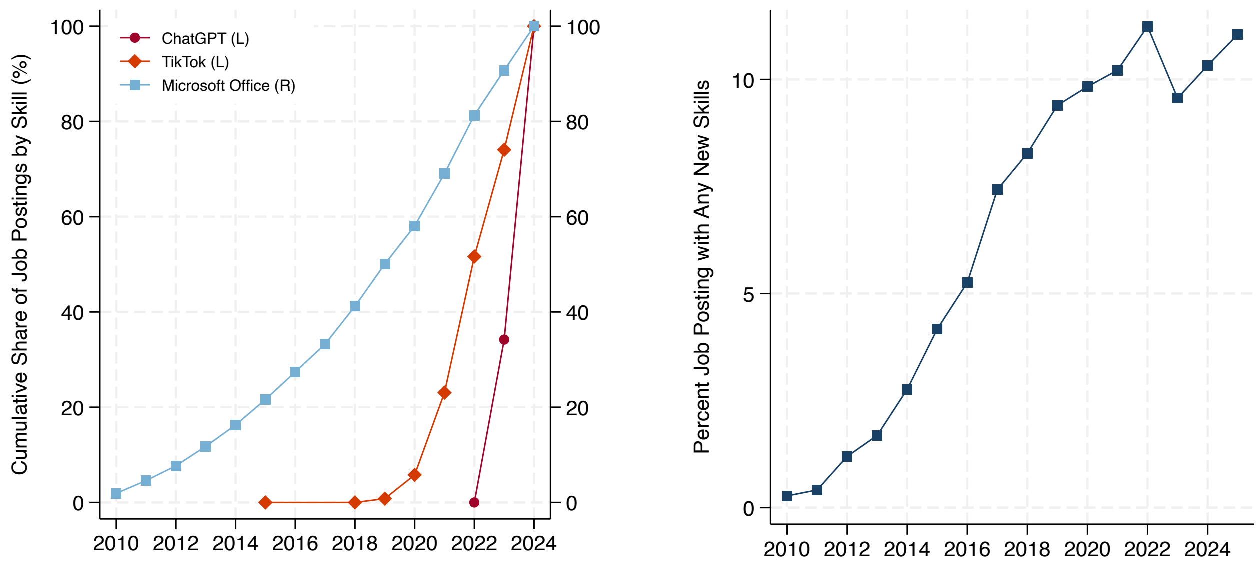
3.1 Measuring New Skills

Data. To study new skills, we primarily use the Lightcast database (formerly "Burning Glass Technologies"), which covers the years 2010 to 2024 for the United States. The data set represents an almost complete set of U.S. online job postings, assembled by systematically scraping more than 220,000 online sources, including major job boards and company career websites (Lightcast 2024). Lightcast converts the raw text of millions of job ads into granular, high-frequency measures of employer demand (with information such as job title, location, and occupation). In addition, it implements a two-stage de-duplication procedure: first flagging newly collected ads, then comparing fields within a 60-day window to eliminate repeated postings. Although Lightcast does not constitute a random sample of vacancies, benchmarking studies show that its U.S. time series and cross-sectional distributions closely track official statistics.[7]

Importantly, Lightcast extracts granular skill requirements directly from vacancy text. Specifically, the database provides a taxonomy of more than 33,000 skills that are continuously updated, and lighcast granular data has been used to analyze patterns in the demand for skills (Deming and Kahn 2018; Hershbein and Kahn 2018; Braxton and Taska 2023).

[7]Based on active postings, Lightcast estimates that since 2013, it has captured on average 92.6 percent of job openings in the Job Openings and Labor Turnover Survey (JOLTS), with a 0.87 correlation between the Lightcast and JOLTS series. It also reports strong alignment with Occupational Employment and Wage Statistics (OEWS) in the distribution of postings by SOC major group (correlation 0.74) and by state (correlation 0.98) from May 2021 to May 2022. Lightcast notes that vacancies not advertised online are often in small firms and union hiring halls (Lightcast 2024).

Figure 1: Illustration of New Skill Definition



(a) Cumulative Share of Job Postings by Skill (%)

(b) Percent of Job Postings with Any New Skills

Notes: Panel (a) shows the cumulative share of job postings listing three specific skills—ChatGPT, TikTok, and Microsoft Office—over the period 2010–2024. Panel (b) displays the percentage of all job postings that require at least one "new skill" (as defined in the text) from 2010 to 2024.

Defining New Skills. We classify a skill as "new" if it was virtually absent at the start of the decade, defined as having less than one percent of its total recorded postings occurring during the 2010–2011 base period, following the methodology of Atalay et al. (2020). The year of emergence of a skill is defined as the first year in which the skill's prevalence exceeds this threshold. To ensure robustness and filter out idiosyncratic noise or rare spelling variations, we further restrict our analysis to skills that appear in at least 100 unique job postings. Under this definition, we identify 2,046 new skills between 2010 and 2024.

Figure 1 illustrates our definition of new skills and documents their rising importance in the labor market. Panel (a) plots the cumulative share of job postings for three illustrative skills: Microsoft Office, TikTok, and ChatGPT. Microsoft Office (blue squares) serves as a counterfactual; its usage accumulates steadily throughout the decade and surpasses the one percent threshold well before our 2010–2011 base period. In contrast, TikTok (orange diamonds) and ChatGPT (red circles) remain virtually absent from the labor market until sharp increases around 2020 and 2022, respectively. These trajectories exemplify our classification criteria: a skill is deemed new only if it was negligible in the base period—accounting for less than one percent of its total postings—and subsequently surged in demand. Aggregating this measure across the economy, Panel (b) shows that the share of job postings requiring at least one such new skill has grown substantially, rising from near zero in 2010 to over 10 percent by 2024.

AI Skills. Within this set of new skills, we further identify those that are considered *AI skills*. Our classification strategy builds upon the framework provided by the Stanford AI Index and the Lightcast AI Skills taxonomy (Maslej et al. 2025). To capture the rapid evolution of technology observed during our sample period, we extend Maslej et al. (2025)'s AI taxonomies by subjecting our list of new skills to an LLM-augmented review. We prompt ChatGPT to rigorously evaluate each new skill against a three-tier rubric: AI Developers (core skills for building AI tools), AI Users (skills for leveraging AI tools), and Non-AI.

Table 1 presents the new skills emerging in Managerial Occupations and Elementary Occupations, along with the years in which each skill first exceeded the 1% and 2% thresholds, respectively, with AI-related skills shaded. The contrast in the nature of these emerging new skills is pronounced. For Managerial Occupations (left Panel), the newly demanded skills are primarily digital and heavily focused on advanced data analytics and cloud computing (such as Tableau, Power BI, and Amazon Web Services), many of which are AI-related (indicated in shades). By contrast, the new skills in Elementary Occupations are qualitatively different. Although there are signs of basic digital pervasion (e.g., Google Drive, Microsoft Edge), the new demands also relate to specific regulatory or specialized certifications. Notably, AI skills are largely absent from the new skill requirements in elementary occupations.

Table 1: Examples of Emerging Skills by Occupation Groups

Managerial Occupations			**Elementary Occupations**		
Skill	**1%**	**2%**	**Skill**	**1%**	**2%**
Tableau (Business Intelligence)	2012	2013	Microsoft Edge	2018	2019
Google Workspace	2012	2013	POCO (C++ Library)	2012	2013
Power BI	2016	2017	Google Drive	2013	2014
Data Science	2013	2014	Class A/B UST Certification	2012	2012
Amazon Web Services	2012	2013	Sustainability Standards	2012	2013
Microsoft Azure	2012	2014	Go Server	2015	2018
Society for HR Management Cert.	2015	2015	Telecom. Device for the Deaf	2013	2014
Zoom (Video Conferencing Tool)	2012	2016	Mechatronics Certification	2013	2014

Notes: Columns "1%" and "2%" report the first year in which the skill's frequency share exceeds the corresponding threshold within the occupation group. AI-related skills are highlighted with a shaded background.

3.2 Content of New and AI Skills

We next analyze the content of new and AI skills by examining their specific constituent categories. Figure 2 presents a heatmap of the relative intensity of different skill categories, defined as the difference between a category's share within the set of new (or AI) skills and the economy-wide share.[8] A positive value indicates that a skill type is disproportionately overrepresented relative to its overall prevalence.

Panels (a) and (b) focus on the composition of new skills. Panel (a) categorizes these skills based on the Lightcast Open Skills taxonomy.[9] Information Technology emerges as the most highly intensive category across the occupational spectrum, particularly for Managers, Professionals, and Technicians. Business and Data Analysis and Social and Administrative skills also exhibit high relative intensity. In contrast, traditional vocational categories such as Architecture and Facilities, and Service and Vocational Studies display negative relative shares across most occupations. To connect these patterns with the task-based literature, Panel (b) maps them onto four Routine/Non-Routine (RNR) groups—Analytical, Interpersonal, Computer, and Routine—following Acemoglu and Autor (2011).[10] This classification confirms the technological bias observed in Panel (a): Computer skills constitute the overwhelming concentration of new skill demand across all occupations. Analytical skills are also prominent, particularly in high-skill occupations, while Routine Manual and Routine Cognitive skills show strong negative values, indicating that the prevalence of new requirements in routine tasks is significantly lower than their overall intensity.

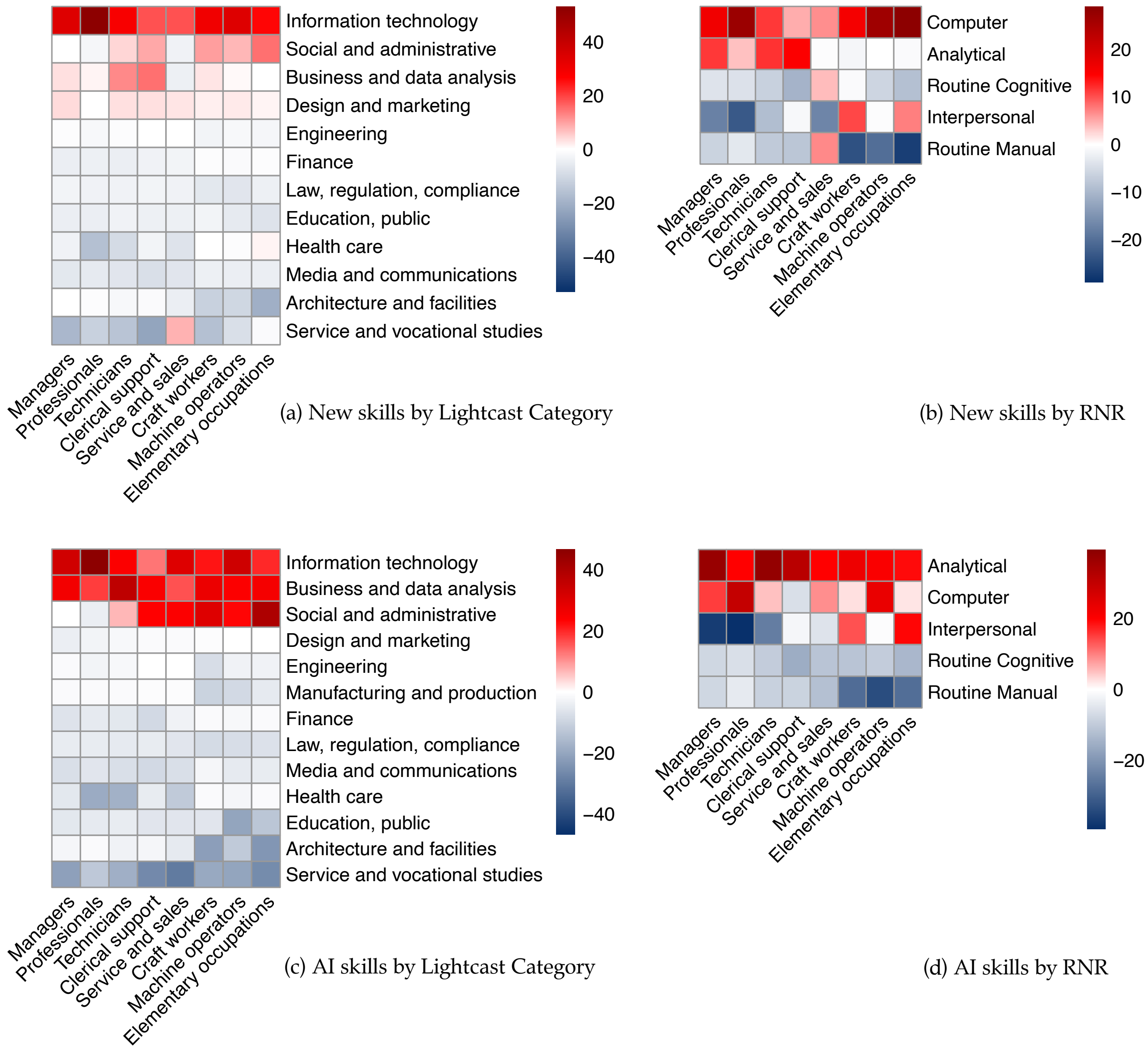
Panels (c) and (d) repeat this analysis for AI-related new skills, which show a more pronounced concentration. In Panel (c), the relative intensity of Information Technology and Business and Data Analysis is even starker. This confirms that the emergence of AI is fundamentally anchored in computational and data-analytic capabilities. Panel (d) confirms this finding through the RNR lens: Analytical and Computer skills are the dominant components of AI demand. Unlike general new skills, where Computer skills were the primary

[8] Normalizing by the economy-wide skill stock filters out pure size effects across skill categories, ensuring that the measure captures skills that are disproportionately represented in new or AI skill demands. The figure displays only those skills where the difference in relative share exceeds one percentage point.

[9] See the Lightcast Open Skills taxonomy documentation (`https://lightcast.io/open-skills/categories`). In this taxonomy, categories are broad groupings that map roughly to career areas (e.g., Information Technology, Finance, and Health Care).

[10] To simplify the skill dimensions, we use the two non-routine skills (analytical and interpersonal) and combine their routine cognitive and manual skills into one. We compute vector embeddings for every Lightcast skill and assign them to the category scoring the highest cosine similarity with representative keywords from Braxton and Taska (2023) and Hershbein and Kahn (2018). See Braxton and Taska (2023) for the specific keywords used.

Figure 2: Relative New and AI Skill Intensity Across Categories



(a) New skills by Lightcast Category

(b) New skills by RNR

(c) AI skills by Lightcast Category

(d) AI skills by RNR

Notes: This figure presents the distribution of new skill types across major occupational groups in the United States, distinguishing four categories of skills based on their emergence and persistence over time. The occupation classification follows International Standard Classification of Occupations (ISCO), with calculations first conducted at the 4-digit level and then averaged at the 1-digit level. Values are expressed in thousands, and declining skills are plotted below the horizontal axis for visual clarity.

driver, AI skills show a dual dominance of both Analytical and Computer competencies. Routine skills, on the other hand, remain strongly negative.

3.3 Wage Regression Sample

For wage analysis, we analyze vacancy-level data from Lightcast, encompassing online job postings in the United States from 2020 through 2024.[11] We first restrict our analysis to postings that report explicit wage information, resulting in a "Full Wage Sample" of 77,682,512 postings. The dataset further provides granular information on occupation (classified via four-digit ISCO or Lightcast specialized codes), industry (six-digit NAICS), and geographic location (county or local authority).[12] To ensure data quality for our empirical specifications, we identify a distinct "Regression Sample" of 53,355,556 postings that contain non-missing information across all these dimensions.

We construct our primary outcome variable, the log of posted hourly wages, by harmonizing reported salaries into a consistent hourly unit. When a posting reports a wage interval, we utilize the midpoint. For non-hourly salary frequencies, we apply Lightcast's standardized conversion methodology: annual salaries are converted to hourly rates by dividing by a fixed factor of 2,080 hours (corresponding to a standard 40-hour workweek over 52 weeks), while monthly and weekly salaries are adjusted using proportional factors. Recent work by Hazell and Taska (2025) validates the use of Lightcast posted wages for labor market analysis, demonstrating that they closely track the average wage for new hires in the Current Population Survey (CPS) at the state, industry, and occupation levels.[13] In Online Appendix A, we show that the occupational distribution of the regression sample closely resembles that in the Occupational Employment and Wage Statistics (OES).

Table 2 reports descriptive statistics for both the full wage sample and the regression subsample, indicating that the two are closely comparable in their observable characteristics. The average hourly wage in the full sample is $30.28, rising slightly to $30.68 in the wage-specific subsample. Approximately 8.5 percent of the full sample and 9.0 percent of the wage sample report at least one new skill; among these postings, the average number of new skills per posting is 2.5. The sample is predominantly high-skill (42–43 percent) and is concentrated in middle-to-high income quintiles, with IT-related new skills appearing in approximately 4 percent of postings.

[11] We restrict our wage analysis to this period due to a substantial improvement in data quality and coverage driven by the recent adoption of pay transparency laws.

[12] Lightcast geo-coded postings to counties and county-equivalent jurisdictions in the United States, yielding 3,141 distinct local areas in our regression sample.

[13] Hazell and Taska (2025) argue that posted wages are accurate because vacancy durations are short, posting costs discourage stale information, and a significant share of workers accept the posted wage without bargaining. Coverage of wage data in online postings has improved significantly in recent years, driven largely by the adoption of pay transparency legislation in various U.S. states.

Table 2: Descriptive Statistics of Job Postings, 2020–2024

	Full Wage Sample	Regression Sample
Number of postings	77,682,512	53,355,556
Mean hourly wage (in $)	30.28	30.68
Average number of skills listed	12.2	12.5
Share reporting at least one new skill	8.5%	9.0%
Average number of new skills listed conditional on having a new skill	2.4	2.5
By occupation type		
High-skill (%)	42.4%	43.6%
White-collar (%)	23.0%	23.3%
Blue-collar (%)	19.3%	19.6%
Low-skill (%)	15.3%	13.6%
By occupational income quintile		
Quintile 1 (lowest-wage occupations)	16.3%	15.7%
Quintile 2	20.2%	20.2%
Quintile 3	29.7%	29.1%
Quintile 4	24.1%	24.9%
Quintile 5 (highest-wage occupations)	9.7%	10.1%
By new skill category (share of all postings)		
IT-related skills (%)	3.9%	4.4%
Business and Data Analysis (%)	2.1%	2.3%
Social / Administrative (%)	1.6%	1.6%
All other skills (%)	2.7%	2.7%

Notes: The table reports descriptive statistics for job postings with non-missing information on wages (full wage sample) and non-missing information on wages, industry (NAICS-2017), occupation (ISCO-08), skills, location, and a firm identifier (regression sample). Wages are converted to hourly rates. A new skill is defined following the definition of Atalay et al. (2020). Occupation types are based on Acemoglu and Autor (2011). The assignment of occupations to occupational income quintiles is defined using OES employment data from 2024 and linked to the job postings using crosswalks between SOC2018, SOC2010, and ISCO-08 occupational classifications.

4 Estimating the Effects of New Skills on Posted Wages

Online job postings provide transparent information about how employers price skill requirements at the point of hire. When a firm posts a vacancy, it simultaneously declares (i) *what it seeks*—the bundle of skills the job will require—and (ii) *what it is willing to pay* to attract applicants who plausibly possess that bundle. This is not the worker-side wage equation familiar from household surveys; it is the employer-side *offer* margin. That distinction matters. Posted wages are imperfect measures of realized pay since we do not observe workers' final salaries after possible negotiations. Yet, the posting margin has an advantage: it allows to observe employer demand for specific skills at enormous scale and fine granularity and to answer the question: *are firms willing to pay more if they seek to fill a position that requires new skills?*

4.1 Empirical Strategy

Let i index a job posting. Our outcome is the log posted wage, $\log(wage_i)$, constructed from the salary information contained in the posting. Our primary regressor, $NewSkill_i$, is an indicator equal to one if posting i lists at least one *new* skill, where "new" is defined as described in Section 3. We estimate the wage premium associated with new skills using the following baseline specification:

$$\log(wage)_i = \beta \cdot NewSkill_i + \delta_{f\times t} + \delta_{occc\times t} + \delta_{region\times t} + \delta_{stype\times t} + \delta_{\#skills} + \epsilon_i, \qquad (1)$$

where $NewSkill_i$ is an indicator equal to one if posting i lists at least one new skill. Fixed effects absorb firm-by-year ($f \times t$), occupation-by-year ($o \times t$), region-by-year ($reg \times t$), and salary-type-by-year ($stype \times t$) variation. In two alternative specifications, we replace the firm-by-year fixed effects ($\delta_{f\times t}$) by either only industry-by-year fixed effects ($\delta_{ind\times t}$) or combined with firm fixed effects (δ_f).[14] We also control for the total number of skills listed in the posting (*#skills*). In all specifications, we cluster standard errors at the local labor market level following the Bureau of Labor Statistics definition used for our regional units (as reported in Table 3). This clustering choice accommodates correlated wage-setting and posting behavior within local labor markets.

[14] We absorb pay-period-by-year fixed effects (e.g., hourly versus annually) so that our estimates do not mechanically reflect changes over time in the composition of postings reporting wages in different units. As the industry of a firm is identical across time and establishments, adding firm $\times$ year fixed effects absorb the industry $\times$ year fixed effects.

As a robustness check, we estimate a more saturated specification in which we interact occupation, industry, and county:

$$\log(wage)_i = \beta \cdot NewSkill_i + \delta_{f\times t} + \delta_{o\times ind\times c\times t} + \delta_{stype\times t} + \delta_{\#skills} + \epsilon_i. \quad (2)$$

Equivalent to the baseline specification, we provide two alternative specifications for our main results in which we replace the firm-by-year fixed effects ($\delta_{f\times t}$) by either only industry-by-year fixed effects ($\delta_{ind\times t}$) or combined with firm fixed effects (δ_f).

All regression setups control for the number of skills listed in the job posting allowing for the following interpretation of the coefficient of interest β: After controlling for detailed fixed effects, is a job posting that lists a new skill associated with a higher posted wage than a comparable job posting that posts instead a skill which is not defined as new?

4.2 Wage effect of the presence of new skills

Table 3 reports our headline finding: vacancies that request new skills systematically offer higher posted wages, and the premium remains significant even in very saturated fixed effect specifications. Column (1) incorporates occupation-by-year, industry-by-year, and region-by-year fixed effects, along with pay-period-by-year effects and fixed effects for the total number of listed skills. Postings that list at least one new skill offer a log wage premium of 0.0628, roughly 6.5 percent higher than average wages. Adding firm fixed effects reduces the premium to 0.0421, implying that part of the differential reflects that high-wage firms are more likely to request new skills (see Column (2)).[15] Results for the baseline specification (1) are reported in Column (3) which includes firm-by-year fixed effects. It yields a comparable estimate (0.0426) indicating that the premium is not driven by time-varying firm wage policies or by firm-level compositional changes across years.

Columns (4) through (6) implement versions of the saturated specification (2) by absorbing detailed industry × occupation × region × year fixed effects. This design compares postings within the same detailed job-market cell in the same year. Under this specification, the premium remains sizable at 0.0340 when no firm fixed effects are added (Column (4)). Adding firm fixed effects in Column (5) and then firm-by-year fixed effects in Column (6) further tightens identification to comparisons within the same firm-year and the same detailed job-market cell. Even in this most demanding specification, the estimated premium

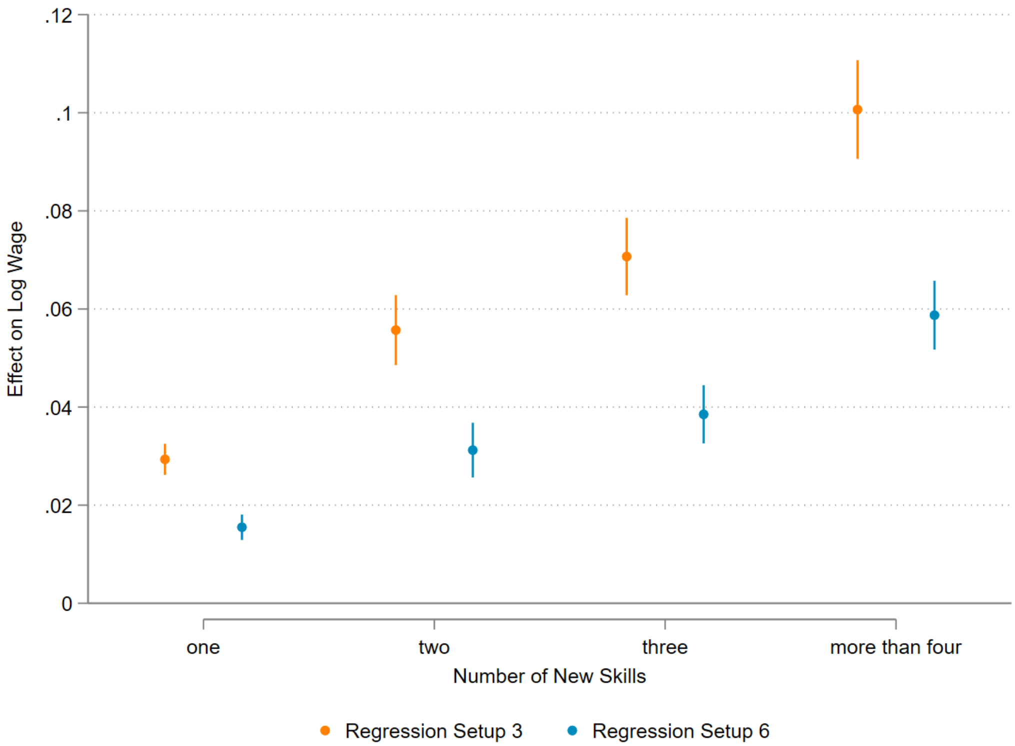
[15] Jaumotte et al. (2026) documents that younger, more innovative, and less credit-constrained firms are more likely to post vacancies requiring new skills, which is consistent with the attenuation of the premium as we absorb firm and firm-by-year fixed effects.

Table 3: Wage Premium to New Skills in Job Postings

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Presence of any New Skill in the Job Posting						
Any new skill	.0628***	.0421***	.0426***	.0340***	.0235***	.0234***
	(.0033)	(.0022)	(.0022)	(.0023)	(.0018)	(.0018)
adjusted R^2	0.650	0.739	0.754	0.791	0.829	0.837
Panel B: Number of New Skills in the Job Posting						
One new skill	.0442***	.0288***	.0293***	.0234***	.0156***	.0155***
	(.0027)	(.0016)	(.0016)	(.0018)	(.0013)	(.0013)
Two new skills	.0795***	.0552***	.0557***	.0437***	.0309***	.0312***
	(.0050)	(.0036)	(.0036)	(.0033)	(.0028)	(.0028)
Three new skills	.1101***	.0690***	.0707***	.0600***	.0385***	.0385***
	(.0055)	(.0041)	(.0040)	(.0036)	(.0030)	(.0030)
Four or more new skills	.1443***	.1034***	.1007***	.0815***	.0603***	.0587***
	(.0068)	(.0052)	(.0051)	(.0041)	(.0036)	(.0036)
adjusted R^2	0.649	0.739	0.754	0.791	0.829	0.837
Fixed Effects						
Firm		X			X	
Firm x Year			X			X
Ind x Year	X	X	(X)			
Occ x Year	X	X	X			
Reg x Year	X	X	X			
Ind x Occ x Reg x Year				X	X	X
Pay-period x Year	X	X	X	X	X	X
Total number of skills	X	X	X	X	X	X
Regression details						
Observations	53,355,556					
Observations absorbed by fixed effects	64	275,554	942,003	6,783,459	7,022,852	7,524,502

Notes: Dependent variable: log of the posted wage. Industry is represented by 6-digit NAICS industry codes, occupation by 4-digit ISCO-08 occupational classification, the regional varibale is at the county level, pay period can be either hourly, daily, weekly, monthly, or annually. Standard errors clustered at the local labor market level are in parentheses. Following the definition of the Bureau of Labor Statistics leads to 1164 distinct local labor markets. *** p-val < 0.001, ** p-val < 0.01, * p-val < 0.05

Figure 3: Number of New Skills in Job Posting and Posted Wages



Note: This figure plots the estimated wage premiums for job postings conditional on the number of new skills listed (one, two, three, or four or more). The analysis uses job postings from 2020–2024 with information on posted wages, skills, 6-digit North American Industry Classification System (NAICS) industry, 4-digit International Standard Classification of Occupations (ISCO) occupation, pay period, county, and year of posting. The dependent variable is the log of the posted hourly wage. The reported coefficients estimate the wage premiums associated with these different new-skill counts, relative to the baseline of postings with zero new skills. The specification controls for fixed effects corresponding to Table 3 column (3) and (6). Standard errors are clustered at the local labor market level.

is 0.0234, about 2.4 percent. Two facts are worth emphasizing. First, the coefficient declines as the fixed effects absorb more variation, which is precisely what one would expect if new skill demand is more prevalent in high-wage firms and high-wage cells. Second, the coefficient stabilizes well above zero even under firm-by-year and saturated cell controls, implying that new skills are priced *within* firms and *within* narrowly comparable jobs.

Panel B replaces the "any new skill" indicator with bins for the number of new skills listed. The gradient is steep and monotone in every column. In the saturated firm-by-year specification (2) in Column (6), a posting that lists exactly one new skill carries a premium of 0.0155 (about 1.6 percent). The premium roughly doubles for two new skills to 0.0312, rises further for three new skills to 0.0385, and reaches 0.0587 (about 6.0 percent) for postings listing four or more new skills. Figure 3 depicts the results of Columns (3) and (6) representing specifications (1) and (2). Conditioning on firm-by-year effects and detailed Industry $\times$ Occupation $\times$ Region $\times$ Year cells forces comparisons among postings that are extremely similar on observables. The remaining monotone gradient suggests that employers price the *intensity* of new-skill requirements, not merely their presence.

4.3 Heterogeneity

We study heterogeneity along occupations and skill types because the wage effects of "new skills" are unlikely to be uniform. Across occupations, the value of a skill depends on the task environment in which it is deployed: a given skill can be strongly complementary to some tasks in some jobs and largely redundant in others. Across skill types, "new" is not itself a structural attribute—technologies and the capabilities they require can both augment workers in some tasks (raising the demand for complementary expertise) and substitute for them in others (reducing the demand for certain forms of expertise), as emphasized in task-based accounts of technological change (Autor and Thompson, 2025; Acemoglu and Restrepo, 2019). This motivates estimating interaction specifications that allow the new-skill effect to vary flexibly by occupation and by skill class (including AI user versus AI developer skills), while preserving the baseline identification strategy.

The heterogeneity specifications are estimated under two benchmark designs which follow the specifications (1) and (2). This makes the heterogeneity results comparable to the results in Columns (3) and (6) in Table 3 as we rely on the same combination of fixed effects. For simplicity, we describe the heterogeneity design associated with the baseline specifications (1) only. We estimate a single interaction specification that allows the pricing of new skills to vary flexibly across heterogeneity type:

$$\log(wage_i) = \sum_{g \in \mathcal{G}} \beta_g \Big(NewSkill_i \times \mathbb{1}\{g(i) = g\} \Big) + \delta_{f \times t} + \delta_{occc \times t} + \delta_{region \times t} + \delta_{stype \times t} + \delta_{\#skills} + \epsilon_i, \tag{3}$$

where $g(i)$ denotes a grouping variable (e.g., occupational income tercile, occupational task category, AI versus non-AI, or the task domain of the new skill). $NewSkill_i$ is the same indicator variable for the presence of a new skill while $\mathbb{1}\{g(i) = g\}$ if any new skill in the job posting belongs to a certain type. In a robustness check, we amend specification (3) through adding saturated Industry × Occupation × Region × Year fixed effects following specification (2). Both specifications condition on firm-year fixed effects absorbing any firm-year wage setting and while focusing on fine labor-market cells and holding the overall required number of skills constant via $\delta_{\#skills}$).

4.3.1 Occupations and Income Terciles

New skills might have different effects on wage premia along the occupational spectrum as well as along the income distribution. To investigate the former, Figure 4 reports occupation-specific estimates of the wage premium to postings that list new skills under specification (3). The premium is positive in every major occupational group, indicating that—even within the same firm and year—vacancies requesting new skills are posted at higher wages than other vacancies. The magnitude, however, varies sharply by occupation. The largest premia accrue to managers (0.05–0.06 log units, about 6 percent), followed by service and sales and professionals, where the premium is on the order of 4–5 percent. Technicians and craft workers exhibit more moderate premia around 3–4 percent, while clerical support and elementary occupations display the smallest effects (roughly 2–3 percent). These gradients seem consistent with heterogeneity in the task content and technology exposure of jobs. At the lower end, the smaller premia may reflect weaker exposure to frontier skill demand in elementary work, and—especially for clerical occupations—greater substitution pressures from automation of routine cognitive tasks, which can compress wage gains even when postings adopt new digital requirements.

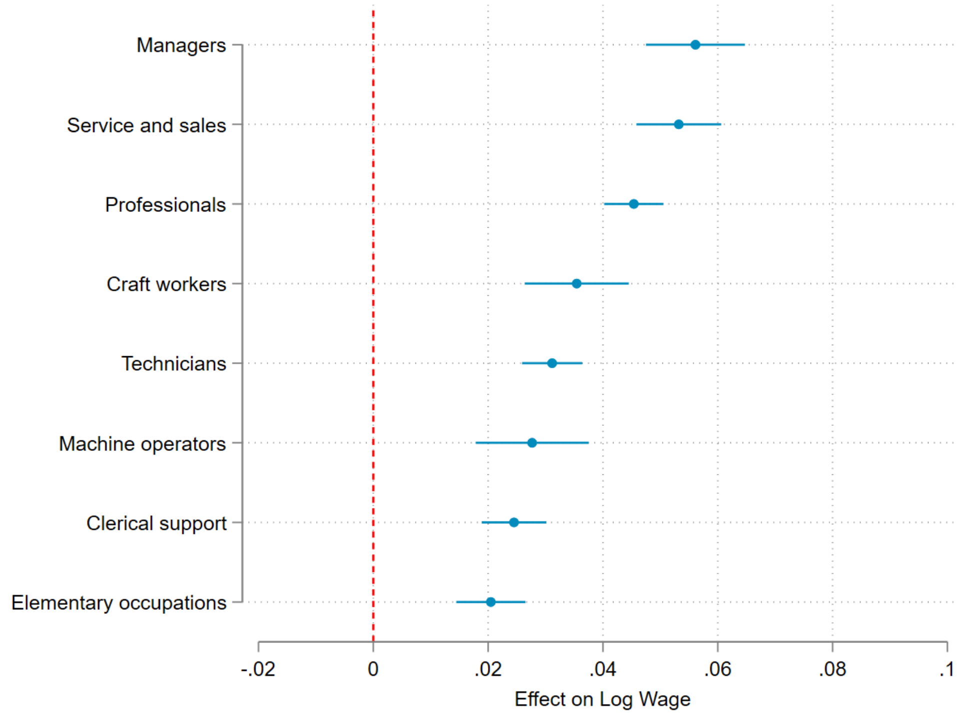
While Figure 4 shows that the new-skill premium is positive across major occupational groups, Columns (1) and (2) in Table 4 group occupations into earnings terciles based on BLS-OEWS average pay (following Batra et al., 2023). Under the baseline specification (3) (Column (1)), the premium is largest in the highest-earning tercile (0.056 log points, about 5.8 percent), smaller but still significant in the lowest tercile (0.034 log points) and in the middle tercile (0.025 log points). Column (2) reports results for the saturated industry$\times$occupation$\times$region$\times$year design which highlights compressed magnitudes while preserving the ranking. Nonetheless, the saturated fixed effects appear to decrease the coefficient of the highest tercile the most to (0.029 log units). Columns (3) and (4) rely on the definition of occupational categories by Autor and Dorn (2013) and show comparable findings: premia are larger in high-skill and white-collar work (0.043–0.045 under the baseline specification (3)) than in blue-collar jobs (0.025), with low-skill occupations in between (0.031). With highly saturated fixed effects, these differences narrow (roughly 0.022–0.027), but the premium remains positive across all categories.

Table 4: Heterogeneity by Occupational Income Terciles and Occupational Categories

	(1)	(2)	(3)	(4)
Panel A: Any New Skill - Occupational Income Terciles				
Lowest Tercile	.0343***	.0230***		
	(.0031)	(.0021)		
Middle Tercile	.0249***	.0125***		
	(.0022)	(.0019)		
Highest Tercile	.0564***	.0292***		
	(.0031)	(.0024)		
Panel B: Any New Skill - Occupational Categories				
High skill			.0434***	.0228***
			(.0027)	(.0020)
White collar			.0453***	.0259***
			(.0028)	(.0020)
Blue collar			.0246***	.0224***
			(.0032)	(.0031)
Low skill			.0311***	.0269***
			(.0039)	(.0043)
Fixed Effects				
Firm x Year	X	X	X	X
Ind x Year	(X)		(X)	
Occ x Year	X		X	
Reg x Year	X		X	
Ind x Occ x Reg x Year		X		X
Pay-period x Year	X	X	X	X
Total number of skills	X	X	X	X
Regression details				
Design in Table 3	(3)	(6)	(3)	(6)
Observations	53,355,556			
Observations absorbed by fixed effects	942,003	7,524,502	942,003	7,524,502
adjusted R^2	0.754	0.837	0.754	0.837

Notes: Dependent variable: log of the posted wage. Industry is represented by 6-digit NAICS industry codes, occupation by 4-digit ISCO-08 occupational classification, the regional varibale is at the county level, pay period can be either hourly, daily, weekly, monthly, or annually. Standard errors clustered at the local labor market level are in parentheses. Following the definition of the Bureau of Labor Statistics leads to 1164 distinct local labor markets. *** p-val < 0.001, ** p-val < 0.01, * p-val < 0.05

Figure 4: Heterogeneity by the 1-digit ISCO Occupations based on Regression (3) in Table 3



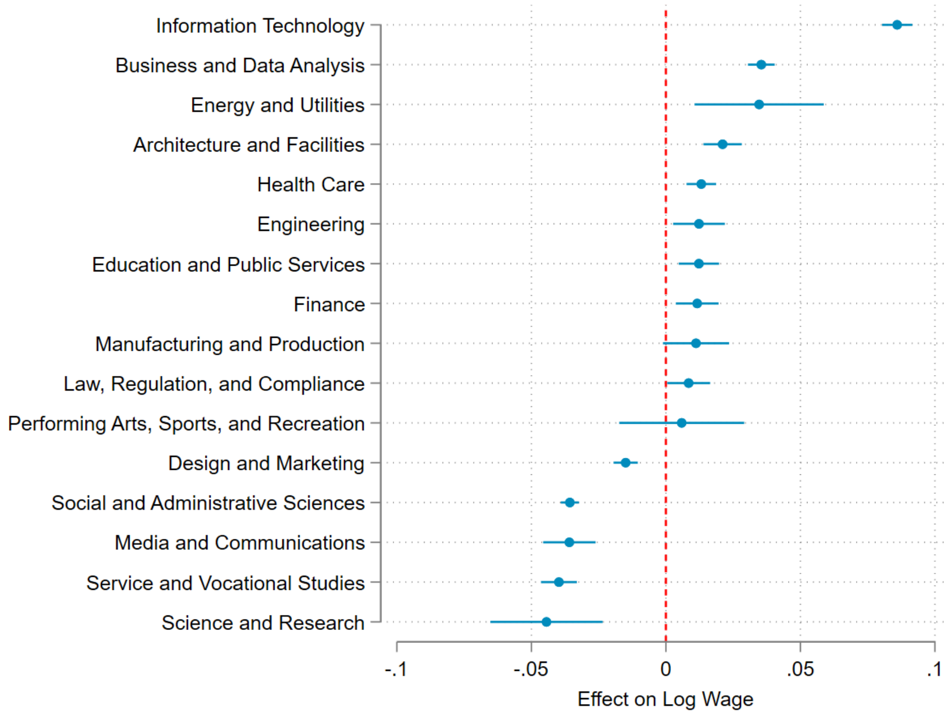
Note: This figure plots the estimated wage premiums for new skills across 1-digit ISCO occupational groups. The analysis uses job postings from 2020–2024 with information on posted wages, skills, 6-digit North American Industry Classification System (NAICS) industry, 4-digit International Standard Classification of Occupations (ISCO) occupation, pay period, county, and year of posting. The dependent variable is the log of the posted hourly wage. Coefficients are derived from interacting the "any new skill" indicator with each major occupation group. The specification controls for firm-by-year, industry-by-year, occupation-by-year, region-by-year, and pay-period-by-year fixed effects, plus the total number of listed skills, corresponding to Table 3 column (3). Standard errors are clustered at the local labor market level.

4.3.2 Skill Type and Related Tasks

The occupation-level patterns in the previous section established that, on average, new-skill requirements receive a wage premium in most parts of the labor market. But they do not specify if any group of skills is a particular driving force. This matters because the set of new skills might be very heterogeneous: some might reflect frontier technical skills complementing high-productivity tasks, while others reflect the adoption of standardized tools or workflow protocols that may routinize work. A task-based view, therefore, predicts heterogeneity not only across jobs but also across *types* of skills, including the possibility that some new skills are associated with flat or even negative wage premia. We therefore decompose new skills into skill types following the Lightcast skill categories (see Figure 2).

Figure 5 shows that the wage premium of new skills varies sharply by its category relying on the baseline specification (3). New Information Technology skills command by far

Figure 5: Heterogeneity by the Lightcast Skill Categories based on Regression (3) in Table 3



Note: This figure plots the estimated wage premiums for new skills across Lightcast skill categories (domains). The analysis uses job postings from 2020–2024 with information on posted wages, skills, 6-digit North American Industry Classification System (NAICS) industry, 4-digit International Standard Classification of Occupations (ISCO) occupation, pay period, county, and year of posting. The dependent variable is the log of the posted hourly wage. Coefficients are derived from interacting the "any new skill" indicator with each skill domain. The specification controls for firm-by-year, industry-by-year, occupation-by-year, region-by-year, and pay-period-by-year fixed effects, plus the total number of listed skills, corresponding to Table 3 column (3). Standard errors are clustered at the local labor market level.

the largest premium, 0.08–0.09 log units (about 9 percent), followed by Business and Data Analysis at about 4-5 percent. A second tier—such as Energy and Utilities and Architecture and Facilities—exhibits moderate positive premia (roughly 2–4 percent), while a broad middle set of domains (e.g., health care, engineering, education/public services, finance, manufacturing, law/compliance) clusters still positive but closer to zero. Strikingly, several categories display negative differentials: postings that list new skills in media and communications, social and administrative sciences, service and vocational studies, and science and research are associated with wage declines on the order of 3–4 percent-which reinforce that listing a new skill is not synonymous with "upskilling": in some domains, new skills may accompany task standardization or automation that shifts demand toward lower-paid task bundles even within the same firm-year.

Panel A of Table 5 emphasizes that the wage premium of new skills is highly uneven when separating new AI skills from new non-AI skills. Under the baseline specification (3)),

Table 5: Heterogeneity by AI Skills and Main Task related to New Skill

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Any New Skill - AI and non-AI Skills						
Any new AI skill	.0737***	.0391***				
	(.0035)	(.0027)				
Any new AI User skill			.0396***	.0140***		
			(.0037)	(.0029)		
Any new AI Developer skill			.0881***	.0572***		
			(.0025)	(.0019)		
Any new non-AI skill	.0280***	.0158***	.0283***	.0160***		
	(.0019)	(.0015)	(.0019)	(.0015)		
Panel B: Any New Skill - Main Task related to New Skill						
Analytical					.0451***	.0205***
					(.0023)	(.0018)
Computer					.0543***	.0327***
					(.0025)	(.0018)
Interpersonal					.0136***	.0050**
					(.0019)	(.0015)
Routine Cognitive					-.0049*	.0173***
					(.0025)	(.0030)
Routine Manual					.0417***	.0233***
					(.0032)	(.0015)
Fixed Effects						
Firm x Year	X	X	X	X	X	X
Ind x Year	(X)		(X)		(X)	
Occ x Year	X		X		X	
Reg x Year	X		X		X	
Ind x Occ x Reg x Year		X		X		X
Pay-period x Year	X	X	X	X	X	X
Total number of skills	X	X	X	X	X	X
Regression details						
Design in Table 3	(3)	(6)	(3)	(6)	(3)	(6)
Observations	53,355,556					
Observations absorbed by fixed effects	942,003	7,524,502	942,003	7,524,502	942,003	7,524,502
adjusted R^2	0.754	0.837	0.754	0.837	0.754	0.837

Notes: Dependent variable: log of the posted wage. Industry is represented by 6-digit NAICS industry codes, occupation by 4-digit ISCO-08 occupational classification, the regional varibale is at the county level, pay period can be either hourly, daily, weekly, monthly, or annually. Standard errors clustered at the local labor market level are in parentheses. Following the definition of the Bureau of Labor Statistics leads to 1164 distinct local labor markets. *** p-val < 0.001, ** p-val < 0.01, * p-val < 0.05

postings that require any new AI skill carry a large premium of 0.074 log units (about 7.6 percent), compared with 0.028 (about 2.8 percent) for new non-AI skills. Tightening the comparison set to the saturated industry×occupation×region×year design compresses these estimates but preserves the ranking: 0.039 (about 4.0 percent) for AI versus 0.016 (about 1.6 percent) for non-AI. Disaggregating AI into user versus developer requirements reveals substantial further heterogeneity. Under the baseline specification (3), AI developer skills command a premium of 0.088 log units, more than double the premium for AI user skills (0.040), consistent with developer capabilities being scarcer and more tightly linked to frontier production processes.

Panel B turns from skill categories to the task content most closely associated with the new skill requirement. New skills tied to computer and analytical tasks are most strongly rewarded (baseline specification (3): 0.054 and 0.045), whereas interpersonal skills carry a much smaller premium (0.014). Two patterns are particularly informative. First, the strong premia for computer and analytical skills align with the earlier evidence that new IT skills are valued most highly. Second, the estimates for routine cognitive skills are close to zero and sensitive to the inclusion of the saturated fixed effects—suggesting that routine cognitive new skills might be especially prone to composition effects across detailed job-market cells. Overall, Table 5 reinforces the central message of the section: the labor market does not attach a uniform return to new skills, but wage premia are heterogeneous-with the largest premia accruing to frontier AI-developing skills as well as general IT skills.

4.3.3 New Job Titles

A second lens on new work focuses on the labels employers use to describe jobs. Job titles are a natural object of interest—titles are salient, portable, and often used as shorthand for a bundle of tasks and expertise. Yet titles are also noisy: firms can post idiosyncratic labels, reuse old labels for new content, and vary in how finely they name roles. To systematically identify new job titles, we start from Lightcast's universe of roughly 73,000 titles and consolidate near-duplicates using a widely used Word2Vec algorithms—the Continuous Bag of Words (CBOW) model—following Kim et al. (2024). Building on Atalay et al. (2020), we then time-stamp titles by tracking when they first become non-trivial in its vacancy distribution. Specifically, we classify a title as new if it crosses the 1st percentile of the job title's cumulative distribution of vacancies for the first time in 2011 or later. This approach separates genuinely new title entries from mere relabeling noise and allows us to ask the question: are wage premia in ''new work'' primarily a function of new titles, or of the new

Table 6: Wage Returns of New Skills and New Job Titles

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Presence of any New Skill in the Job Posting						
Emerging job title	-.0002	-.0076***	-.0071***	-.0033***	-.0038***	-.0032***
	(.0011)	(.0009)	(.0009)	(.0009)	(.0007)	(.0007)
Any new skill	.0588***	.0389***	.0397***	.0323***	.0215***	.0215***
	(.0031)	(.0020)	(.0021)	(.0022)	(.0017)	(.0017)
Any new skill x	.0336***	.0324***	.0304***	.0167***	.0179***	.0166***
Emerging job title	(.0026)	(.0021)	(.0020)	(.0019)	(.0018)	(.0017)
adjusted R^2	.650	.740	.755	.791	.830	.837
Fixed Effects						
Firm		X			X	
Firm x Year			X			X
Ind x Year	X	X	(X)			
Occ x Year	X	X	X			
Reg x Year	X	X	X			
Ind x Occ x Reg x Year				X	X	X
Pay-period x Year	X	X	X	X	X	X
Total number of skills	X	X	X	X	X	X
Regression details						
Benchmark design in Table 3	(1)	(2)	(3)	(4)	(5)	(6)
Observations			51,393,950			
Observations absorbed by fixed effects	66	274,480	935,898	6,642,431	6,880,479	7,376,027

Notes: Dependent variable: log of the posted wage. Industry is represented by 6-digit NAICS industry codes, occupation by 4-digit ISCO-08 occupational classification, the regional varibale is at the county level, pay period can be either hourly, daily, weekly, monthly, or annually. Standard errors clustered at the local labor market level are in parentheses. Following the definition of the Bureau of Labor Statistics leads to 1164 distinct local labor markets. *** p-val < 0.001, ** p-val < 0.01, * p-val < 0.05

skills employers request within those titles?

Table 6 delivers a striking result: wage premia are driven by new skills and not by new job titles. Across specifications, the direct effect of a new job title is small and, once controls are introduced, slightly negative. In the most demanding specification in Column (6), a new title is associated with a wage differential of -0.0032 log units (about -0.3 percent), despite being precisely estimated. By contrast, the premium to listing new skills remains large and stable: the coefficient on is 0.0215 in column (6) (about 2.2 percent), closely mirroring the baseline estimates in Table 3. The interaction term shows where new titles matter: they amplify the return to new skills. In column (6), postings that list both a new title and at least one new skill have an additional premium of 0.0166 (about 1.7 percent) on top of the baseline new-skill wage premium. Taken together, these estimates imply that new titles, by themselves, do not command higher pay; rather, the wage premium in new-title jobs is earned through the skill content. Quantitatively, the implied premium for a posting that combines a new title with at least one new skill is approximately 0.035 log units in the tightest specification.

4.4 Robustness

This section tests the robustness of our baseline estimates along three dimensions: the measurement of new skills, inference, and sample composition.[16] Across all exercises, the central finding—that postings requiring new skills command higher wages—remains quantitatively and qualitatively intact.

First, we consider alternative definitions of new skills. Our baseline classification relies on a percentile-based threshold in the skill distribution. In this section, we consider two alternative thresholds: 0.5 percent and 2 percent. Tables A2 and A3 show that the estimated wage premia are nearly identical when we instead use these two alternative "new skill" definitions, confirming that the results are not sensitive to the precise cutoff used. We also adopt a more time-based definition, classifying skills as new if they appear for the first time after 2011, either unconditionally (Table A4) or within a three-year rolling window (Table A5). The sign, monotonicity by the number of new skills, and economic interpretation of the new-skill wage premium are stable. Under these alternative definitions focusing on skills appearing for the first time after 2011, the estimated premia are, if anything, larger than in the baseline. This is consistent with imposing greater weight on more recently introduced and less diffused skills, which might be closer to the technological frontier and more scarce.

Second, we assess whether our results are sensitive to the level of statistical aggregation used for inference. Table A6 reports results using multi-way clustered standard errors at the local labor market level and at the intersection of 4-digit ISCO occupations and 6-digit NAICS industries. While this adjustment modestly increases standard errors, the point estimates remain reassuringly highly statistically significant across all specifications.

[16] In all robustness exercises, the sample is kept constant, as in our baseline, except when an alternative sample is analyzed.

Third, we assess whether our estimates are influenced by postings placed by staffing and recruiting intermediaries rather than by the ultimate hiring employer. Table A7 repeats our main specifications after excluding vacancies posted by industries whose primary business is to place or supply workers to client firms[17]. This restriction addresses a distinct measurement concern: intermediary postings may reflect recruiter screening practices and templated language, and the firm identifier in the vacancy may correspond to the intermediary rather than the wage-setting client, weakening the mapping from listed skills to underlying job requirements. Consistent with the central role of intermediaries in online hiring markets, recruitment and staffing firms account for a large share of vacancy postings on major platforms (Davis and Samaniego de la Parra, 2024). Reassuringly, while the estimated new-skill premium attenuates in the restricted sample, it remains positive and precisely estimated across specifications, indicating that our core conclusions are not driven by vacancies posted by intermediaries.

A final concern with online vacancy data is that many postings report wages in broad intervals rather than precise values, raising the possibility that measured wage differentials reflect reporting practices rather than genuine price differences. To address this issue, Table A8 restricts the sample to postings that report a point wage, following approaches in the recent vacancy literature that emphasize measurement precision in posted compensation (e.g., Hazell and Taska, 2025). This restriction reduces the sample size substantially but leaves the qualitative conclusions unchanged. The estimated premium for listing any new skill remains positive and statistically significant across all specifications, though it is attenuated relative to the baseline (column (6): 0.0135 log units versus 0.0234 in the full sample). The monotonic pattern with respect to the number of new skills is also preserved: postings requiring more new skills command progressively higher wages, with economically large premia for postings listing three or more new skills. The attenuation is consistent with the idea that point-wage postings may come from firms with more standardized pay-setting practices or tighter internal wage bands, potentially compressing observed dispersion. Importantly, the persistence of the premium in this more precisely measured subsample indicates that our findings are not driven by the use of broad wage intervals and instead reflect genuine differences in the market valuation of new skills.

[17] We drop job postings associated with firms that indicate to be in the following industries: *Employment Placement Agencies (NAICS Code 561311)*, *Executive Search Services (NAICS Code 561312)*, *Temporary Help Services (NAICS Code 561320)*, and *Human Resources Consulting Services (NAICS Code 541612)*

5 The Role of Breakthrough Technological Innovations

In this section, we examine how technological shocks drive the emergence of new skills and influence their wage returns. Our analysis focuses specifically on *breakthrough* innovations—technologies that represent radical departures from prior ones. Because these discontinuous leaps are largely unanticipated, they offer a source of variation that is plausibly exogenous to pre-existing labor market trends (Autor et al. 2024). We first construct a measure of exposure to these breakthrough technologies using patent text data linked to skill definitions. We then leverage this measure to document the heterogeneity in returns to new skills and to instrument for shifts in new skill demand within a 2SLS framework.

5.1 Skill-Level Exposure to Breakthrough Innovations

To empirically assess the impact of technological shocks, we rely on patent data from the USPTO PatentsView database. We distinguish high-impact, novel technologies from standard inventions by applying the text-based methodology of Kelly et al. (2021a). This approach utilizes natural language processing (NLP) of patent abstracts to measure innovation based on textual similarity. Specifically, a patent is classified as a "breakthrough" if it exhibits low textual similarity to all preceding patents (indicating novelty) but high similarity to subsequent patents within 5 years (indicating impact), suggesting the beginning of a new technological trajectory. Following Kelly et al. (2021a), we define a patent as a "breakthrough" if its computed breakthrough score falls within the top 10th percentile of the distribution for the set of patents we observed from 2010 to 2016.[18]

Next, we map these patent-level innovations to the Lightcast skill taxonomy using high-dimensional vector embeddings. We generate embeddings for the abstracts of all identified breakthrough patents and for the descriptions in the Lightcast skill taxonomy.[19] We then calculate the cosine similarity between these patent and skill embeddings to identify the specific skills associated with each breakthrough patent. We consider a skill to be linked to a patent only if their cosine similarity score is above a threshold of 0.45.

[18] In Kelly et al. (2021a), the breakthrough score is defined as the log ratio of a patent's similarity with future innovations (forward 5-year aggregate) to its similarity with past technologies (backward 5-year aggregate).

[19] Unlike static models such as Continuous Bag of Words (CBOW), which predict target words from local context windows, we employ a transformer-based embedding model that produces context-sensitive representations for full text spans. We compute 3,072-dimensional embeddings using OpenAI's `text-embedding-3-large` model to capture semantic similarity beyond simple co-occurrence.

5.2 Job Postings, New Skills, and related Patents

Table 7 presents the key facts motivating our patent-based heterogeneity analysis and instrumental variable design: while general patent exposure is pervasive across job postings, the presence of new skills directly linked to patents is significantly rarer, thereby offering a source of informative variation.

In the full regression sample, the mapping from skills to patents is dense. Nearly nine in ten postings (88.4 percent) list at least one skill that can be linked to a patent, and the average posting contains 4.62 patent-linked skills. This reflects the broad reach of patented technologies into ordinary job requirements—many postings mention skills (software, methods, tools) that are technologically "traceable" even when the job itself is not at the frontier.

The subset of postings that list any new skill—about 9 percent of the wage sample—looks even more technology-intensive: 97.9 percent of these postings contain at least one patent-linked skill, and they list more than twice as many linked skills on average (10.52). Put differently, postings that demand novel skills are overwhelmingly drawn from parts of the labor market whose required skill bundles are closely connected to patented technologies.

Crucially, however, the patent linkages that matter for identification are not the ubiquitous links to any skill, but the linkages to new skills. Only 36.5 percent of new-skill postings contain at least one new skill that is patent-linked, and the average number of patent-linked new skills is just 0.58. The distribution is thin: about one quarter of new-skill postings have exactly one patent-linked new skill (25.8 percent), and very few have four or more (roughly 2 percent combined). This sparsity is precisely what makes patent-linked new skills a useful shifter for the presence of new skills: it isolates a component of skill novelty that is plausibly tied to upstream innovation rather than to general job requirements or relabeling.

The same pattern appears when we count associated patents. While postings are linked to many patents through their overall skill bundle (44.8 on average in the full sample), postings with new skills have substantially higher patent association (136.5). Yet patents associated specifically with new skills remain limited (2.9 on average), and extreme exposure is rare (e.g., fewer than 1 percent of new-skill postings are linked to 50+ patents via new skills). Taken together, these facts imply that patent exposure is nearly universal at the level of overall skill bundles, but breakthrough-patent exposure through newly emerging skills is comparatively rare and sharply varying.

Table 7: Descriptive Statistics of Job Postings and Skill-related Patents

Regression Sample	All Job Postings Patents linked to any skill	Job Postings with New Skills Patents linked to any skill	 Patents linked to new skills
Skills linked to at least one Patent in Job Postings			
Average number of linked (new) skills	4.62	10.52	0.58
Share of postings with at least one (new) skill linked to a patent (in %)	88.4	97.9	36.5
Share of job postings (in %) with ...			
... one linked (new) skill	15.3	3.6	25.8
... two linked (new) skills	13.5	4.6	5.7
... three linked (new) skills	11.8	5.4	2.6
... four linked (new) skills	9.7	6.2	1.3
... $\geq$ five linked (new) skills	38.1	78.2	0.7
Patents associated to Job Postings			
Average number of associated patents	44.8	136.5	2.9
Share of job postings with more than ...			
... five associated patents	67.1	92.2	12.3
... ten associated patents	57.2	87.7	7.4
... 20 associated patents	44.1	79.7	3.8
... 50 associated patents	24.1	62.3	0.8
... 100 associated patents	12.4	42.9	0.1
... 200 associated patents	4.6	22.0	0.0
Overall sample			
Share within regression sample	100.0%	9.0 %	

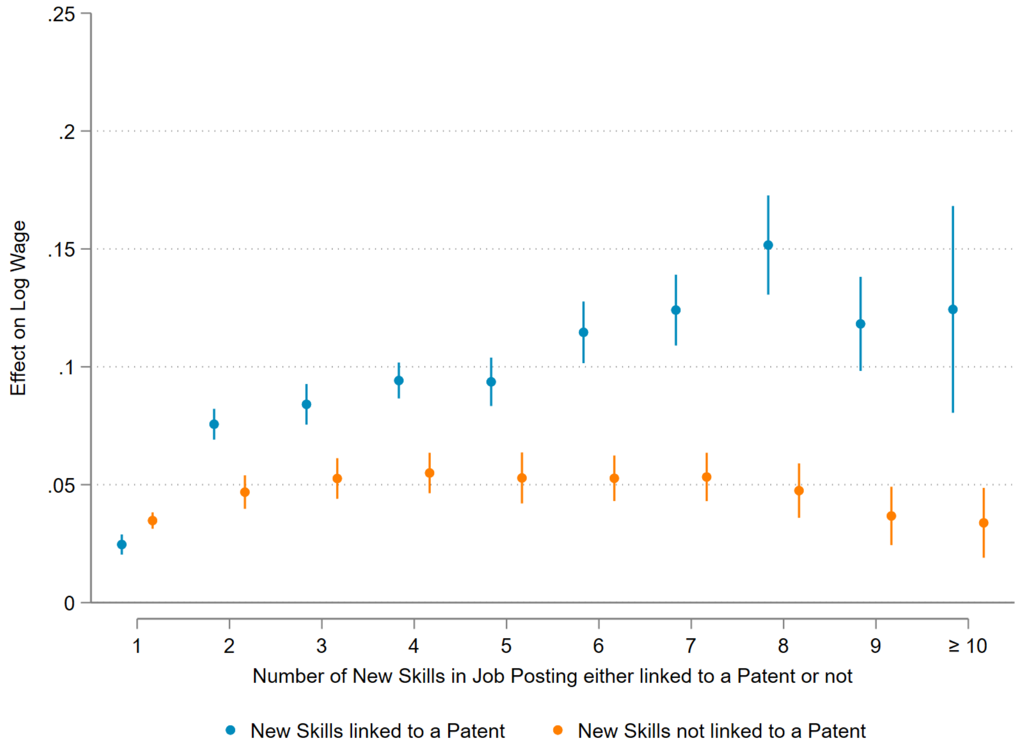
Notes: The table reports descriptive statistics for job postings which are linked through their skills to breakthrough patents as explained in . The definition of breakthrough patents relies on Kelly et al. (2021b). A new skill is defined following the definition of Atalay et al. (2020). The sample is restricted to the regression sample, i.e., job postings with non-missing information on wages, industry (NAICS-2017), occupation (ISCO-08), skills, location, and a firm identifier.

5.3 Implications for Wage Returns

Heterogeneity in Returns by Patent Linkage. Figure 6 examines how the wage premium for new skills varies with their link to breakthrough innovations. It reports estimates from a specification that interacts the "any new skill" indicator with the count of new skills in the posting that are explicitly linked to breakthrough patents as well as counts of non-linked new skills. This approach decomposes the overall premium by the intensity of exposure to radical technological change.

The results reveal a striking gradient: the returns on new skills are substantially higher

Figure 6: Heterogeneity by Number of New Skills in the Job Posting linked to any Patent based on Regression (3) in Table 3



Note: This figure plots the estimated wage premiums for job postings containing new skills, conditional on the number of those skills linked to breakthrough patents and the number of new skills not linked to breakthrough patents. The analysis uses job postings from 2020–2024. The dependent variable is the log of the posted hourly wage. The x-axis represents the count of new skills in a posting that are textually linked to breakthrough patents (defined as the top 10th percentile of novelty). The reported coefficients estimate the wage premium associated with this patent linkage intensity, relative to postings without new skills. The specification controls for firm-by-year, occupation-by-year, region-by-year, and pay-period-by-year fixed effects, plus the total number of listed skills, corresponding to the design in Table 3 column (3). Standard errors are clustered at the local labor market level.

when those skills are directly associated with breakthrough innovations. For postings listing new skills that are not linked to any breakthrough patent, the premium hovers around 4-6 percent independent of the amount of skills. However, as the number of patent-linked new skills increases, the wage premium rises sharply. For instance, the premium jumps to about 8 percent with just two patent-linked skills and exceeds 12 percent for postings with seven or more. This monotonic increase suggests that the economic value of new skills has a significant association with their connection to technological innovations, consistent with the view that breakthrough technologies are linked to productivity growth.

5.4 Instrumental Variable Estimates

To isolate the variation driven specifically by technological innovation and address potential measurement error in the definition of new skills, we estimate a Two-Stage Least Squares (2SLS) specification. We instrument the "any new skill" indicator with the number of breakthrough patents linked to the skills listed in the posting during the 2010 to 2016 period. This instrument captures the pre-determined technological content of the skills, isolating the component of demand that stems from exposure to radical innovation.

Table 8 presents the results. Across all specifications, the results confirm that new skill

Table 8: IV Estimates of Wage Premium to New Skills

	(1)	(2)
Panel A: IV using Sum of Patents (Unweighted)		
Any new skill	.2198***	.1062**
	(.0249)	(.0353)
Kleibergen-Paap F-stat	1390.9	791.6
Panel B: IV using Sum of Patents (Citation Weighted)		
Any new skill	.4811***	.4866***
	(.0763)	(.1018)
Kleibergen-Paap F-stat	132.4	97.2
Fixed Effects		
Firm x Year	X	X
Occ x Year	X	
Reg x Year	X	
Ind x Occ x Reg x Year		X
Pay-period x Year	X	X
Total number of skills	X	X
Regression details		
Observations	52,413,553	45,831,054
Observations absorbed by fixed effects	942,003	7,524,502

Notes: Dependent variable: log of the posted wage. Panel A reports IV estimates using the unweighted sum of patents in 2010 as the instrument. Panel B reports estimates using citation-weighted patent counts. Column (1) corresponds to the main design (Table 3 column (3)). Column (2) corresponds to the saturated robustness check (Table 3 column (6)).Industry is represented by 6-digit NAICS industry codes, occupation by 4-digit ISCO-08 occupational classification, the regional varibale is at the county level, pay period can be either hourly, daily, weekly, monthly, or annually. Standard errors clustered at the local labor market level are in parentheses. Following the definition of the Bureau of Labor Statistics leads to 1164 distinct local labor markets. *** p-val < 0.001, ** p-val < 0.01, * p-val < 0.05

demand driven by radical technological innovation generates substantial wage gains. In Panel A, which uses the unweighted patent count, we find a wage premium of 24.6 percent in our preferred specification, compared to the OLS estimate of 4.3 reported in Table 3. This premium remains robust even in the saturated specification (Column 2), where we compare postings within the same detailed industry-occupation-region-year cell, returning a wage premium of 11.1 percent. Panel B weights the instrument by forward citations to capture the economic value of the underlying innovations, and this produces even larger estimates of around 62-63 percent (coefficients of 0.481 and 0.487). Across all specifications, the Kleibergen-Paap F-statistics (ranging from 97.2 to 1390.9) reject the null hypothesis of weak instruments, indicating that past patenting activity is a strong predictor of current demand for new skills.

Discussion. The larger magnitude of the IV estimates relative to the OLS baseline aligns with the evidence in Figure 6: wage returns to new skills are highly heterogeneous. Skills explicitly linked to breakthrough innovations yield wage premiums exceeding 10-15 percent, whereas "unlinked" new skills offer much smaller returns. By design, our instrument isolates variation in skill demand driven by upstream technological change (patents), placing more weight on high-value, productivity-enhancing skills and filtering out lower-value shifts. Moreover, the IV strategy addresses potential attenuation bias, suggesting that our baseline OLS results represent a conservative lower bound for the returns to technology-driven new skill demand.

6 Conclusion

We document that the U.S. labor market attaches a significant wage premium to newly emerging skills, particularly when they reflect frontier technological capabilities. Using a near-universe of online job postings, we find that vacancies requiring new skills offer 2–4 percent higher wages than comparable postings within the same firm and detailed job cell, with larger premiums for IT and AI-developer skills. Crucially, we show that this premium to novelty is not driven by rebranding, but by the substantive content of the work because new job titles yield no, or even slightly negative returns. Furthermore, by linking skill demands to patent text, we demonstrate that these returns are anchored in exposure to breakthrough innovations, establishing that the labor market explicitly prices the expertise required to adopt frontier technologies.

These findings open several avenues for future research. First, while we focus on the returns to new skills, a natural counterpart is to investigate the lifecycle of returns to established or "legacy" skills. Second, we isolate new skills linked to frontier technological innovation (breakthrough patents), yet future work could fruitfully examine how non-technological shocks shape the demand for and pricing of novel human capital.

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Appendix for Online Publication

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A ADDITIONAL DESCRIPTIVES

Table A1: Comparing Job Postings with Employment data

	Wage Sample	Regression Sample	OES Sample
By occupation type			
High-skill (%)	42.4%	43.6%	41.5%
White-collar (%)	23.0%	23.3%	17.8%
Blue-collar (%)	19.3%	19.6%	20.8%
Low-skill (%)	15.3%	13.6%	19.4%
By occupational income quintile			
Quintile 1 (lowest-wage occupations)	16.3%	15.7%	19.4%
Quintile 2	20.2%	20.2%	20.9%
Quintile 3	29.7%	29.1%	25.7%
Quintile 4	24.1%	24.9%	21.5%
Quintile 5 (highest-wage occupations)	9.7%	10.1%	12.6%

Notes: The table reports descriptive statistics for job postings with non-missing information on wages (wage sample) and non-missing information on wages, industry (NAICS-2017), occupation (ISCO-08), skills, location, and a firm identifier. Wages are converted to hourly rates. A new skill is defined following the definition of Atalay et al. (2020). Occupation types are based on Acemoglu and Autor (2011). The assignment of occupations to occupational income quintiles is defined using OES employment data from 2024 and linked to the job postings using crosswalks between SOC2018, SOC2010, and ISCO-08 occupational classifications. Employment shares are computed using OES employment data from 2024.

B ADDITIONAL ROBUSTNESS CHECKS

Table A2: Robustness: Alternative new skill definition using a 0.5% threshold

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Presence of any New Skill in the Job Posting						
Any new skill	.0608***	.0415***	.0410***	.0325***	.0227***	.0221***
	(.0030)	(.0022)	(.0022)	(.0021)	(.0017)	(.0017)
adjusted R^2	.648	.739	.754	.791	.829	.837
Panel B: Number of New Skills in the Job Posting						
One new skill	.0419***	.0283***	.0281***	.0223***	.0158***	.0153***
	(.0027)	(.0017)	(.0017)	(.0018)	(.0014)	(.0014)
Two new skills	.0883***	.0583***	.0581***	.0466***	.0302***	.0298***
	(.0044)	(.0035)	(.0035)	(.0030)	(.0024)	(.0025)
Three new skills	.1075***	.0720***	.0701***	.0553***	.0387***	.0374***
	(.0049)	(.0041)	(.0041)	(.0031)	(.0029)	(.0028)
Four or more new skills	.1294***	.0914***	.0868***	.0692***	.0495***	.0472***
	(.0065)	(.0051)	(.0050)	(.0035)	(.0031)	(.0031)
adjusted R^2	.648	.739	.754	.791	.829	.837
Fixed Effects						
Firm		X			X	
Firm x Year			X			X
Ind x Year	X	X	(X)			
Occ x Year	X	X	X			
Reg x Year	X	X	X			
Ind x Occ x Reg x Year				X	X	X
Pay-period x Year	X	X	X	X	X	X
Total number of skills	X	X	X	X	X	X
Regression details						
Design in Table 3	(1)	(2)	(3)	(4)	(5)	(6)
Observations	53,355,556					
Observations absorbed by fixed effects	64	275,554	942,003	6,783,459	7,022,852	7,524,502

Notes: Dependent variable: log of the posted wage. Industry is represented by 6-digit NAICS industry codes, occupation by 4-digit ISCO-08 occupational classification, the regional varibale is at the county level, pay period can be either hourly, daily, weekly, monthly, or annually. Standard errors clustered at the local labor market level are in parentheses. Following the definition of the Bureau of Labor Statistics leads to 1164 distinct local labor markets. *** p-val < 0.001, ** p-val < 0.01, * p-val < 0.05

Table A3: Robustness: Alternative new skill definition using a 2% threshold

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Presence of any New Skill in the Job Posting						
Any new skill	.0628***	.0421***	.0426***	.0340***	.0235***	.0234***
	(.0033)	(.0022)	(.0022)	(.0023)	(.0018)	(.0018)
adjusted R^2	.648	.739	.754	.791	.829	.837
Panel B: Number of New Skills in the Job Posting						
One new skill	.0401***	.0271***	.0279***	.0221***	.0154***	.0153***
	(.0025)	(.0014)	(.0015)	(.0017)	(.0012)	(.0012)
Two new skills	.0665***	.0416***	.0422***	.0336***	.0212***	.0215***
	(.0042)	(.0028)	(.0028)	(.0027)	(.0022)	(.0022)
Three new skills	.0988***	.0628***	.0645***	.0540***	.0358***	.0362***
	(.0058)	(.0045)	(.0044)	(.0040)	(.0034)	(.0035)
Four or more new skills	.1371***	.0965***	.0937***	.0750***	.0542***	.0527***
	(.0066)	(.0051)	(.0051)	(.0040)	(.0036)	(.0036)
adjusted R^2	.648	.739	.754	.791	.829	.837
Fixed Effects						
Firm		X			X	
Firm x Year			X			X
Ind x Year	X	X	(X)			
Occ x Year	X	X	X			
Reg x Year	X	X	X			
Ind x Occ x Reg x Year				X	X	X
Pay-period x Year	X	X	X	X	X	X
Total number of skills	X	X	X	X	X	X
Regression details						
Design in Table 3	(1)	(2)	(3)	(4)	(5)	(6)
Observations			53,355,556			
Observations absorbed by fixed effects	64	275,554	942,003	6,783,459	7,022,852	7,524,502

Notes: Dependent variable: log of the posted wage. Industry is represented by 6-digit NAICS industry codes, occupation by 4-digit ISCO-08 occupational classification, the regional varibale is at the county level, pay period can be either hourly, daily, weekly, monthly, or annually. Standard errors clustered at the local labor market level are in parentheses. Following the definition of the Bureau of Labor Statistics leads to 1164 distinct local labor markets. *** p-val < 0.001, ** p-val < 0.01, * p-val < 0.05

Table A4: Robustness: Alternative new skill definition using skills appearing for the first time after 2011

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Presence of any New Skill in the Job Posting						
Any new skill	.0915***	.0650***	.0631***	.0503***	.0383***	.0375***
	(.0041)	(.0033)	(.0032)	(.0026)	(.0024)	(.0023)
adjusted R^2	.648	.739	.754	.791	.829	.837
Panel B: Number of New Skills in the Job Posting						
One new skill	.0838***	.0595***	.0586***	.0460***	.0355***	.0352***
	(.0038)	(.0032)	(.0031)	(.0026)	(.0025)	(.0025)
Two new skills	.1083***	.0734***	.0697***	.0578***	.0406***	.0390***
	(.0051)	(.0041)	(.0040)	(.0029)	(.0026)	(.0025)
Three new skills	.1099***	.0814***	.0773***	.0610***	.0472***	.0457***
	(.0060)	(.0043)	(.0041)	(.0029)	(.0025)	(.0025)
Four or more new skills	.1179***	.0881***	.0818***	.0668***	.0529***	.0509***
	(.0073)	(.0051)	(.0049)	(.0037)	(.0033)	(.0033)
adjusted R^2	.648	.739	.754	.791	.829	.837
Fixed Effects						
Firm		X			X	
Firm x Year			X			X
Ind x Year	X	X	(X)			
Occ x Year	X	X	X			
Reg x Year	X	X	X			
Ind x Occ x Reg x Year				X	X	X
Pay-period x Year	X	X	X	X	X	X
Total number of skills	X	X	X	X	X	X
Regression details						
Design in Table 3	(1)	(2)	(3)	(4)	(5)	(6)
Observations	53,355,556					
Observations absorbed by fixed effects	64	275,554	942,003	6,783,459	7,022,852	7,524,502

Notes: Dependent variable: log of the posted wage. Industry is represented by 6-digit NAICS industry codes, occupation by 4-digit ISCO-08 occupational classification, the regional varibale is at the county level, pay period can be either hourly, daily, weekly, monthly, or annually. Standard errors clustered at the local labor market level are in parentheses. Following the definition of the Bureau of Labor Statistics leads to 1164 distinct local labor markets. *** p-val < 0.001, ** p-val < 0.01, * p-val < 0.05

Table A5: Robustness: Alternative new skill definition using skill appearing for the first time after 2011 within a 3-year rolling window

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Presence of any New Skill in the Job Posting						
Any new skill	.1046***	.0723***	.0701***	.0583***	.0427***	.0420***
	(.0042)	(.0032)	(.0031)	(.0024)	(.0022)	(.0022)
adjusted R^2	.648	.739	.754	.791	.829	.837
Panel B: Number of New Skills in the Job Posting						
One new skill	.0982***	.0673***	.0661***	.0542***	.0395***	.0393***
	(.0038)	(.0031)	(.0030)	(.0024)	(.0022)	(.0023)
Two new skills	.1178***	.0783***	.0741***	.0652***	.0453***	.0437***
	(.0051)	(.0039)	(.0038)	(.0028)	(.0024)	(.0024)
Three new skills	.1203***	.0903***	.0857***	.0695***	.0548***	.0529***
	(.0059)	(.0041)	(.0040)	(.0031)	(.0025)	(.0025)
Four or more new skills	.1260***	.0935***	.0867***	.0740***	.0582***	.0560***
	(.0070)	(.0047)	(.0044)	(.0033)	(.0030)	(.0029)
adjusted R^2	.648	.739	.754	.791	.829	.837
Fixed Effects						
Firm		X			X	
Firm x Year			X			X
Ind x Year	X	X	(X)			
Occ x Year	X	X	X			
Reg x Year	X	X	X			
Ind x Occ x Reg x Year				X	X	X
Pay-period x Year	X	X	X	X	X	X
Total number of skills	X	X	X	X	X	X
Regression details						
Design in Table 3	(1)	(2)	(3)	(4)	(5)	(6)
Observations	53,355,556					
Observations absorbed by fixed effects	64	275,554	942,003	6,783,459	7,022,852	7,524,502

Notes: Dependent variable: log of the posted wage. Industry is represented by 6-digit NAICS industry codes, occupation by 4-digit ISCO-08 occupational classification, the regional varibale is at the county level, pay period can be either hourly, daily, weekly, monthly, or annually. Standard errors clustered at the local labor market level are in parentheses. Following the definition of the Bureau of Labor Statistics leads to 1164 distinct local labor markets. *** p-val < 0.001, ** p-val < 0.01, * p-val < 0.05

Table A6: Robustness: Multi-way Clustering of Standard Errors at the local labor market level and the 4-digit Isco occupation X 6-digit NAICS industry group

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Presence of any New Skill in the Job Posting						
Any new skill	.0628***	.0421***	.0426***	.0340***	.0235***	.0234***
	(.0047)	(.0036)	(.0036)	(.0040)	(.0033)	(.0033)
adjusted R^2	.648	.739	.754	.791	.829	.837
Fixed Effects						
Firm		X			X	
Firm x Year			X			X
Ind x Year	X	X	(X)			
Occ x Year	X	X	X			
Reg x Year	X	X	X			
Ind x Occ x Reg x Year				X	X	X
Pay-period x Year	X	X	X	X	X	X
Total number of skills	X	X	X	X	X	X
Regression details						
Design in Table 3	(1)	(2)	(3)	(4)	(5)	(6)
Observations	53,355,556					
Observations absorbed by fixed effects	64	275,554	942,003	6,783,459	7,022,852	7,524,502

Notes: Dependent variable: log of the posted wage. Industry is represented by 6-digit NAICS industry codes, occupation by 4-digit ISCO-08 occupational classification, the regional varibale is at the county level, pay period can be either hourly, daily, weekly, monthly, or annually. Multi-way Clustering of Standard Errors at the local labor market level and the 4-digit Isco occupation X 6-digit NAICS industry group. SE are in parenthesis. Following the definition of the Bureau of Labor Statistics leads to 1164 distinct local labor markets. *** p-val < 0.001, ** p-val < 0.01, * p-val < 0.05

Table A7: Robustness: Restricting the sample to non-HR staffing firms

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Presence of any New Skill in the Job Posting						
Any new skill	.0531***	.0302***	.0302***	.0221***	.0109***	.0103***
	(.0034)	(.0020)	(.0020)	(.0021)	(.0015)	(.0015)
adjusted R^2	.640	.738	.755	.796	.835	.844
Fixed Effects						
Firm		X			X	
Firm x Year			X			X
Ind x Year	X	X	(X)			
Occ x Year	X	X	X			
Reg x Year	X	X	X			
Ind x Occ x Reg x Year				X	X	X
Pay-period x Year	X	X	X	X	X	X
Total number of skills	X	X	X	X	X	X
Regression details						
Design in Table 3	(1)	(2)	(3)	(4)	(5)	(6)
Observations	44,255,322					
Observations absorbed by fixed effects	69	274,271	936,926	6,424,289	6,662,304	7,160,110

Notes: Dependent variable: log of the posted wage. Industry is represented by 6-digit NAICS industry codes, occupation by 4-digit ISCO-08 occupational classification, the regional varibale is at the county level, pay period can be either hourly, daily, weekly, monthly, or annually. Standard errors clustered at the local labor market level are in parentheses. Following the definition of the Bureau of Labor Statistics leads to 1164 distinct local labor markets. *** p-val < 0.001, ** p-val < 0.01, * p-val < 0.05

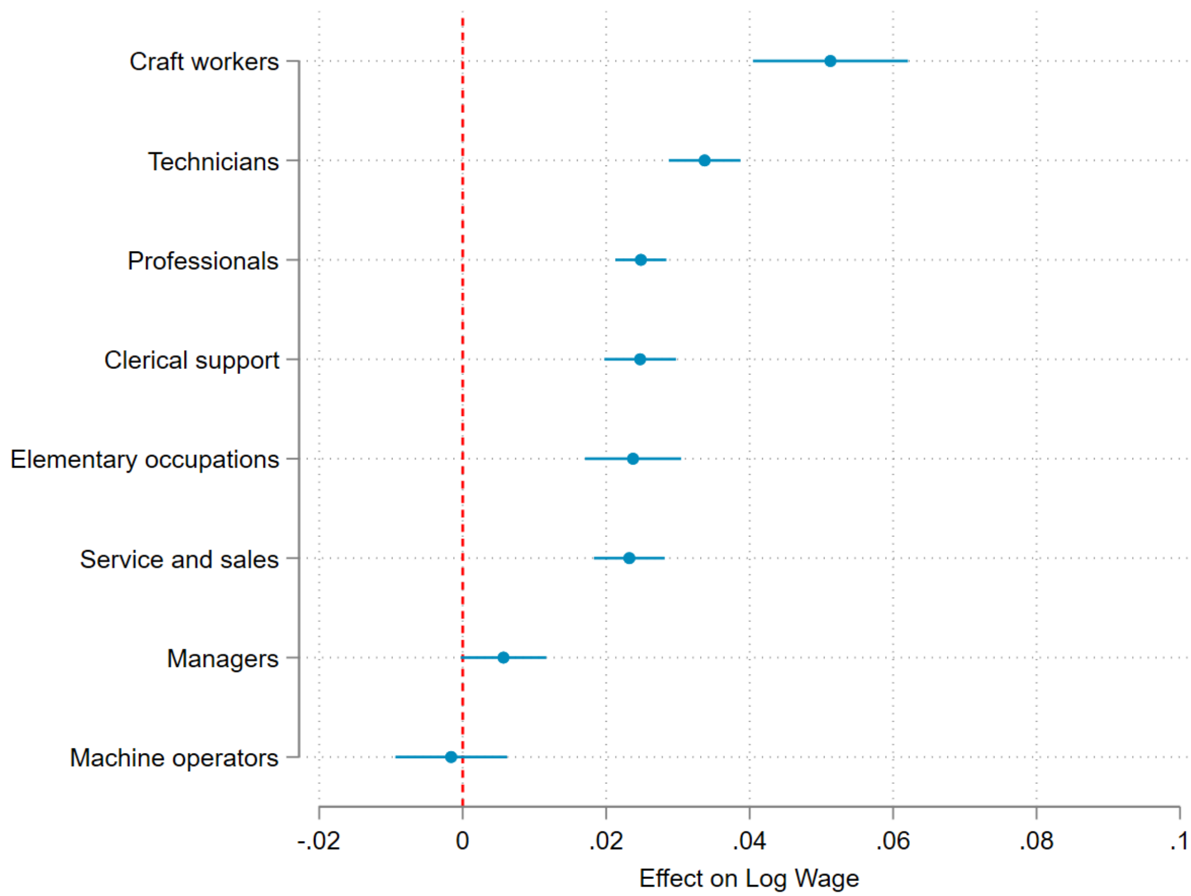
Table A8: Robustness: Restricting the sample to wage postings with a posted point wage

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Presence of any New Skill in the Job Posting						
Any new skill	.0467***	.0285***	.0306***	.0150***	.0130***	.0135***
	(.0029)	(.0019)	(.0020)	(.0024)	(.0016)	(.0016)
adjusted R^2	.623	.753	.775	.828	.871	.880
Panel B: Number of New Skills in the Job Posting						
One new skill	.0205***	.0149***	.0168***	.0044*	.0062***	.0069***
	(.0027)	(.0017)	(.0017)	(.0022)	(.0014)	(.0014)
Two new skills	.0892***	.0531***	.0563***	.0374***	.0278***	.0282***
	(.0054)	(.0035)	(.0035)	(.0039)	(.0028)	(.0028)
Three new skills	.1523***	.0691***	.0727***	.0606***	.0351***	.0341***
	(.0065)	(.0057)	(.0060)	(.0057)	(.0045)	(.0047)
Four or more new skills	.1950***	.1200***	.1194***	.0863***	.0629***	.0619***
	(.0099)	(.0082)	(.0086)	(.0063)	(.0049)	(.0050)
adjusted R^2	.623	.753	.775	.828	.871	.880
Fixed Effects						
Firm		X			X	
Firm x Year			X			X
Ind x Year	X	X	(X)			
Occ x Year	X	X	X			
Reg x Year	X	X	X			
Ind x Occ x Reg x Year				X	X	X
Pay-period x Year	X	X	X	X	X	X
Total number of skills	X	X	X	X	X	X
Regression details						
Design in Table 3	(1)	(2)	(3)	(4)	(5)	(6)
Observations			18,094,393			
Observations absorbed by fixed effects	199	187,367	474,749	3,039,139	3,162,080	3,311,195

Notes: Dependent variable: log of the posted wage. Industry is represented by 6-digit NAICS industry codes, occupation by 4-digit ISCO-08 occupational classification, the regional varibale is at the county level, pay period can be either hourly, daily, weekly, monthly, or annually. Standard errors clustered at the local labor market level are in parentheses. Following the definition of the Bureau of Labor Statistics leads to 1164 distinct local labor markets. *** p-val < 0.001, ** p-val < 0.01, * p-val < 0.05

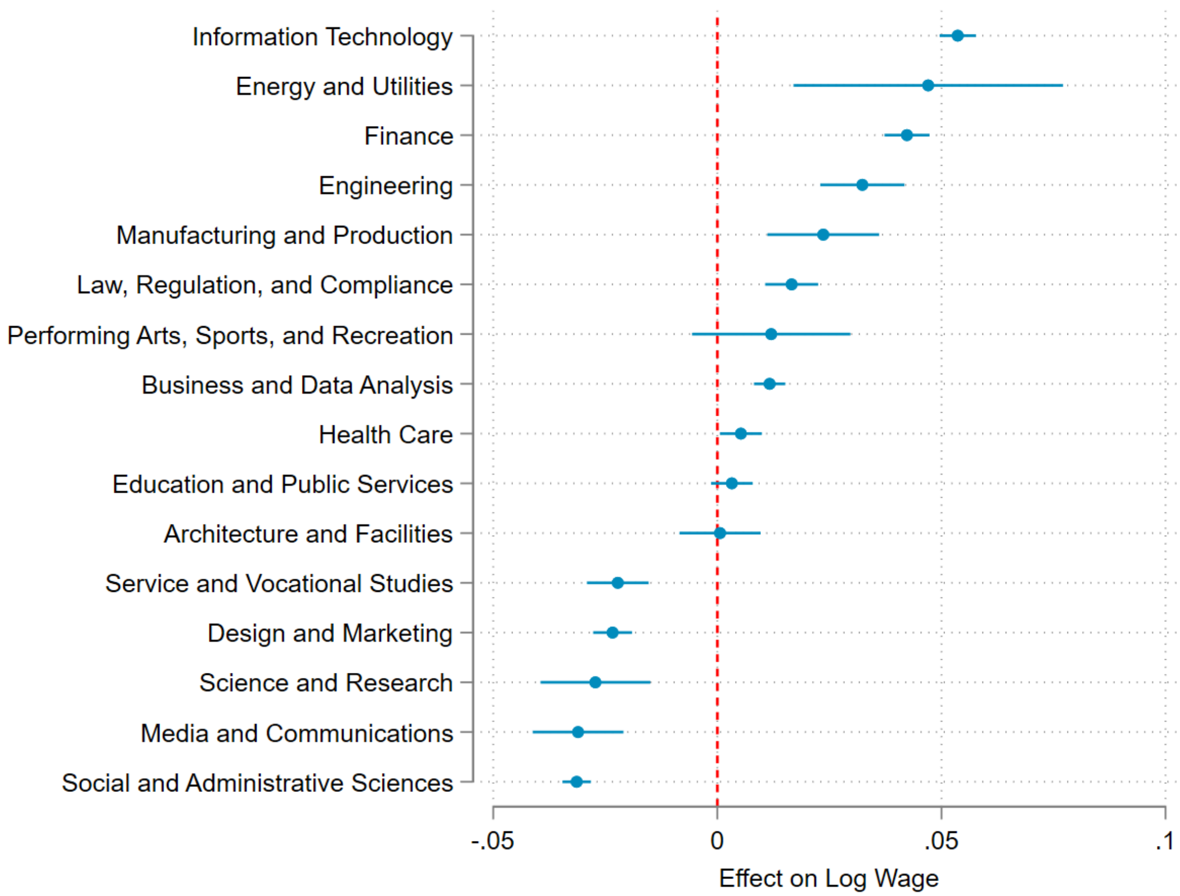
C ADDITIONAL HETEROGENEITY RESULTS

Figure B1: Heterogeneity by the 1-digit ISCO Occupations based on Regression Setup 6



Note: This figure plots the estimated wage premiums for new skills across 1-digit ISCO occupational groups. The analysis uses job postings from 2020–2024 with information on posted wages, skills, 6-digit North American Industry Classification System (NAICS) industry, 4-digit International Standard Classification of Occupations (ISCO) occupation, pay period, county, and year of posting. The dependent variable is the log of the posted hourly wage. Coefficients are derived from interacting the "any new skill" indicator with each major occupation group. The specification controls for fixed effects corresponding to Table 3 column (6). Standard errors are clustered at the local labor market level.

Figure B2: Heterogeneity by the Lightcast Skill Taxonomy based on Regression Setup 6



Note: This figure plots the estimated wage premiums for new skills across Lightcast skill categories (domains). The analysis uses job postings from 2020–2024 with information on posted wages, skills, 6-digit North American Industry Classification System (NAICS) industry, 4-digit International Standard Classification of Occupations (ISCO) occupation, pay period, county, and year of posting. The dependent variable is the log of the posted hourly wage. Coefficients are derived from interacting the "any new skill" indicator with each skill domain. The specification controls for fixed effects corresponding to Table 3 column (6). Standard errors are clustered at the local labor market level.