Supporting Information for *Complement or Substitute? How AI Increases the Demand for Human Skills*

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This supplementary appendix provides additional detail on the data, variables, models, and robustness checks used in the analysis.

S1. The Data

Following prior work, we assume that employers' online vacancy postings reflect evolving skill demands and valuations (1, 2). We leverage a dataset of approximately 10 million (n=9,998,342) U.S. online job postings from January 2018 to December 2023, created by Lightcast and provided by the Burning Glass Institute (BGI). These postings are scraped from over 65,000 websites—including job boards, company career pages, and aggregators (Lightcast Data, n.d.)—capturing the "near-universe" of online vacancies (1). Each posting contains information such as job title, occupation category, salary, and a detailed skill list derived from the text.

Lightcast data have previously facilitated studies on technology's labour market effects (e.g., 1, 3, 4, 5, 6, 7). Extensive tests confirm that Lightcast data mirror U.S. vacancy trends from the Job Openings and Labor Turnover Survey (JOLTS) and the Bureau of Labor Statistics (BLS), and the dataset aligns closely with state-level BLS statistics (Tables S1–S2). Although there is some overrepresentation of professional and technical occupations relative to blue-collar jobs—an established characteristic of online postings data (8) — our focus on knowledge work and comparative skill shares minimises any potential biases.

State	OJV Data	BLS Data
Alabama	1.3%	1.5%
Alaska	0.3%	0.3%
Arizona	2.7 %	2.1%
Arkansas	0.6%	0.9%
California	12.9%	9.4%
Colorado	2.8 %	2.4%
Connecticut	1.1%	1.0%
Delaware	0.3%	0.3%
Florida	6.2%	6.5%
Georgia	3.2%	3.7%
Hawaii	0.4%	0.3%
Idaho	0.6%	0.6%
Illinois	4.0%	4.2%
Indiana	2.0%	1.8%
Iowa	1.0%	0.9%
Kansas	1.0%	0.8%
Kentucky	1.1%	1.3%
Louisiana	1.0%	1.5%
Maine	0.3%	0.5%
Maryland	1.8%	2.0%
Massachusetts	3.0%	2.7%
Michigan	2.9%	2.7%
Minnesota	2.0%	2.1%
Mississippi	0.5%	0.9%
Missouri	1.9%	1.9%
Montana	0.3%	0.4%
Nebraska	0.7%	0.6%
Nevada	1.1%	1.0%
New Hampshire	0.5%	0.5%
New Jersey	2.5%	2.4%
New Mexico	0.6%	0.6%
New York	4.5%	4.8%
North Carolina	3.3%	3.6%
North Dakota	0.2%	0.3%
Ohio	3.6%	3.6%
Oklahoma	1.1%	1.3%
Oregon	1.5%	1.3%
Pennsylvania	3.4%	4.0%
Rhode Island	0.4%	0.3%
South Carolina	1.2%	1.9%
South Dakota	0.3%	0.3%
Tennessee	2.0%	2.5%
Texas	8.6%	8.6%
Utah	1.0%	1.0%
Vermont	0.2%	0.2%
Virginia	3.0%	3.1%
Washington	2.6%	1.8%
Washington D. C.	0.7%	0.4%
West Virginia	0.3%	0.6%
Wisconsin	2.0%	2.1%
Wyoming	0.1%	0.2%

Table S1. Job Openings by State - Comparing Online Job Vacancies (OJV) Data to Bureau of Labor Statistics (BLS) Data. Information leveraging the closest publicly available comparative data for job openings by state: *Job Openings by State (2023)*. (OJV data excludes “District of Columbia” which are included in the BLS dataset. Consequently, shares for BLS in the table are scaled accordingly, to ensure comparability.

Occupation Category (SOC 2)	OJV Data	BLS Data
Architecture and Engineering Occupations	2.3%	1.6%
Arts, Design, Entertainment, Sports, and Media Occupations	2.4%	1.4%
Building and Grounds Cleaning and Maintenance Occupations	2.1%	3.0%
Business and Financial Operations Occupations	7.6%	6.5%
Community and Social Service Occupations	1.6%	1.7%
Computer and Mathematical Occupations	8.4%	3.3%
Construction and Extraction Occupations	1.7%	4.0%
Educational Instruction and Library Occupations	2.9%	7.2%
Farming, Fishing, and Forestry Occupations	0.2%	0.3%
Food Preparation and Serving Related Occupations	4.9%	8.6%
Healthcare Practitioners and Technical Occupations	12.6%	6.6%
Healthcare Support Occupations	3.4%	4.7%
Installation, Maintenance, and Repair Occupations	3.9%	3.8%
Legal Occupations	0.6%	0.8%
Life, Physical, and Social Science Occupations	1.4%	1.0%
Management Occupations	9.9%	6.8%
Office and Administrative Support Occupations	9.3%	12.1%
Personal Care and Service Occupations	1.4%	2.0%
Production Occupations	3.4%	5.4%
Protective Service Occupations	1.2%	2.4%
Sales and Related Occupations	10.4%	8.3%
Transportation and Material Moving Occupations	6.8%	8.6%

Table S2. Occupational Category Composition - Comparing Online Job Vacancies (OJV) Data to Bureau of Labor Statistics (BLS) Data
Information leveraging the closest publicly available comparative data for job openings by occupational category: *Employment by occupational category (2023)*. (BLS data excludes "unclassified occupations" and "military occupations" which are included in the OJV dataset. Consequently, shares for OJV in the table are scaled accordingly, to ensure comparability).

S2. Sample Construction

This section describes the procedures used for identifying AI roles and skills clusters.

S2.A. Defining Skills

To classify complementary and substitutable skills, we consulted the literature (e.g., 9, 10, 11, 12, 13, 14). From this review, we form seven complementary skills clusters: “Analytical Thinking”, “Digital Literacy”, “Resilience”, “Technical Proficiency”, “Ethics”, “Working with Others”, and “Self-Efficiency”. For “substitutable” skills we extract four clusters: “Summary and Reporting”, “Language and Text Review”, “Customer Service”, and “Office and Financial Administration”. While the literature also proposes “Basic Data Skills”, “Information Management”, and “Prediction and Forecasting”, these are not included in our final “substitutable” skills clusters, as we believe these types of skills are likely to co-occur with AI requirements. To illustrate, “Prediction and Forecasting” may be required for data scientists using AI, and equally, AI researchers need coworkers to manage company information. The final skills clusters, alongside the corresponding literature references are presented in Tables S3 and S4.

Skill	**Literature Review (non-exhaustive)**
Analytical thinking	(15, 16, 17, 18)
Digital literacy	(18, 19)
Resilience	(17, 18, 20)
Technical proficiency	(18, 21, 22)
Ethics	(23, 24, 25, 26)
Working with others	(15, 27, 18)
Self-efficiency	(27, 18)

Table S3. “Complementary” Skills Clusters. Consulting the literature, we select seven skills clusters to capture AI-complementing skills in our analyses.

Skill	**Literature Review (non-exhaustive)**
Summary and reporting	(28, 29)
Language and text review	(30, 31, 32)
Customer service	(33, 34, 35, 36)
Office and financial administration	(37, 38, 18)

Table S4. “Substitutable” Skills Clusters. Consulting the literature, we select four skills clusters to capture AI-substitutable skills in our analyses.

We proceed by identifying specific skills within the Lightcast taxonomy. We embed all skills with more than 1000 related posts, as well as each of the category titles with "all-mpnet-base-v2" from the Sentence Transformer library. For each category, we select relevant skills from 10 skills with the highest cosine similarity. It should be highlighted that skills within a category have vastly different occurrence rates. Tables S5 and S6 list all of the skills found for the "complementary" and "substitutable" skills categories, as well as the number of postings mentioning each skill and our decision of whether or not to include a given skill in our analysis. If a job description includes at least one skill from a skill cluster, it is classified as requiring that given skill cluster. This threshold minimises sample loss (see Figure S1) and aligns with prior research (4, 39).

Complementary Group	Skill	Count	Included
Analytical Thinking	Problem Solving	1108795	True
Analytical Thinking	Critical Thinking	273688	True
Analytical Thinking	Systems Thinking	6764	True
Analytical Thinking	Creative Thinking	29065	True
Analytical Thinking	Strategic Thinking	56005	True
Analytical Thinking	Analytical Skills	266223	True
Analytical Thinking	Independent Thinking	12969	True
Analytical Thinking	Intelligence Analysis	4706	True
Analytical Thinking	Creative Problem Solving	37994	True
Analytical Thinking	Analytical Thinking	32338	True
Digital Literacy	Digital Content	8124	True
Digital Literacy	Digital Arts	1201	False
Digital Literacy	Digital Capabilities	2398	True
Digital Literacy	Information Literacy	1221	True
Digital Literacy	Educational Technologies	9478	False
Digital Literacy	Literacy	14192	False
Digital Literacy	Digital Literacy	4206	True
Digital Literacy	Computer Literacy	664990	True
Digital Literacy	Health Literacy	1321	False
Digital Literacy	Digital Acumen	1166	True
Resilience	Tactfulness	128776	True
Resilience	Courage	16828	True
Resilience	Preparedness	4426	True
Resilience	Disaster Preparedness	2564	False
Resilience	Ingenuity	9511	True
Resilience	Tenacity	15986	True
Resilience	Healing	1892	False
Resilience	Resilience	62862	True
Resilience	Resourcefulness	79478	False
Resilience	Survivability	1572	True
Technical Proficiency	Study Skills	2106	False
Technical Proficiency	Technical Training	42819	True
Technical Proficiency	Analytical Skills	266223	False
Technical Proficiency	Mechanical Aptitude	57640	True
Technical Proficiency	Technical Subject Matter	5436	True
Technical Proficiency	Diagnostic Skills	4111	True
Technical Proficiency	Digital Acumen	1166	True
Technical Proficiency	Fine Motor Skills	111080	False
Technical Proficiency	Technical Acumen	55124	True
Technical Proficiency	Competency Assessment	5333	True
Ethics	Honesty	120982	True
Ethics	Confidentiality	372250	False
Ethics	Professional Responsibility	3203	True
Ethics	Business Ethics	14730	True
Ethics	Medical Ethics	8246	False
Ethics	Personal Integrity	24973	True
Ethics	Nursing Ethics	1243	False
Ethics	Ethical Standards And Conduct	303842	True
Ethics	Accountability	330622	True
Ethics	Compassion	123864	False
Working with Others	Interdisciplinary Collaboration	2700	True
Working with Others	Teamwork	474835	True
Working with Others	Delegation Skills	13083	True
Working with Others	Collaborative Communications	1609	True
Working with Others	Collaboration	133059	True
Working with Others	Team Building	87719	True
Working with Others	Cross-Functional Collaboration	10986	True
Working with Others	Team Processes	4299	True
Working with Others	Partner Development	2623	True
Working with Others	Support Colleagues	1052	True
Self-Efficiency	Self-Awareness	14216	True
Self-Efficiency	Self-Motivation	413397	True
Self-Efficiency	Self-Control	6464	True
Self-Efficiency	Self-Sufficiency	4780	True
Self-Efficiency	Self-Discipline	81260	True
Self-Efficiency	Business Efficiency	1162	True
Self-Efficiency	Conscientiousness	17643	True
Self-Efficiency	Resourcefulness	79478	True
Self-Efficiency	Operational Efficiency	27450	False
Self-Efficiency	Self-Regulation	1157	False

Table S5. "Complementary" Skills Clusters Matched with Lightcast Skills Taxonomy. For each of the seven "complementary" skill clusters, we match skills from the Lightcast taxonomy, and record whether the given skill is included in the final set of skills used to identify "complementary" skill in the analysis. We further report the number of job postings mentioning each skill.

Substitute Group	Skill	Count	Included
Summary and Reporting	Management Reporting	32834	True
Summary and Reporting	Report Creation	2247	True
Summary and Reporting	Report Development	5148	True
Summary and Reporting	Report Analysis	1609	True
Summary and Reporting	Statistical Reporting	14162	False
Summary and Reporting	Operational Reporting	4375	True
Summary and Reporting	Business Reporting	6120	True
Summary and Reporting	Report Building	1312	True
Summary and Reporting	Reporting and Analysis	10849	True
Summary and Reporting	Reports Analysis	1345	True
Language and Text Review	Language Arts	5201	True
Language and Text Review	Writing Systems	27337	True
Language and Text Review	Reviewing Applications	2408	True
Language and Text Review	Code Review	40232	False
Language and Text Review	Document Review	8125	True
Language and Text Review	English Language	635617	True
Language and Text Review	Foreign Language	9874	True
Language and Text Review	Language Development	2150	True
Language and Text Review	Multilingualism	197313	True
Language and Text Review	Written English	22707	True
Customer Service	Customer Service	2622996	True
Customer Service	Customer Service Desk	3276	True
Customer Service	Healthcare Customer Service	1342	True
Customer Service	Sales Support	46062	True
Customer Service	Client Services	34742	True
Customer Service	Support Services	65689	True
Customer Service	Technical Support	96506	True
Customer Service	Customer Support	77539	True
Customer Service	Customer Service Training	3611	True
Customer Service	Customer Service Management	4955	True
Office and Financial Administration	Financial Services	125245	False
Office and Financial Administration	Office Management	63841	True
Office and Financial Administration	Certified Management Accountant	1103	False
Office and Financial Administration	Bookkeeping	71591	True
Office and Financial Administration	Sales Administration	3291	True
Office and Financial Administration	Accounting Management	3851	True
Office and Financial Administration	Business Administration	133334	True
Office and Financial Administration	Office Administration	17956	True
Office and Financial Administration	Accounting	472847	False
Office and Financial Administration	Financial Management	60884	False

Table S6. “Substitutable” Skills Clusters Matched with Lightcast Skills Taxonomy. For each of the four “substitutable” skill clusters, we match skills from the Lightcast taxonomy, and record whether the given skill is included in the final set of skills used to identify “substitutable” skill in the analysis. We further report the number of job postings mentioning each skill.

S2.B. Defining AI-related Roles

The analysis relies on the distinction between AI-related and non-AI roles (i.e. positions working with AI technologies, and positions which do not. Following a skills-based approach (3, 4, 10), we identify AI-related roles by the presence of at least one AI skill requirement in the job posting. This method avoids misclassifying non-AI positions within AI-focused firms (e.g., a Human Resources Manager at an AI company) as AI roles.

We use the list of skills in Lightcast's "Artificial Intelligence and Machine Learning (AI/ML)" subcategory as our sample of AI skills, with the exception of the generic terms "Artificial Intelligence" and "Machine Learning", which may be associated with the company description. The complete set of skills in this subcategory, as well as the number of job postings mentioning each skill, and our decision on whether to include the skill in the analysis, are shown in Table S7. Figure S1 further displays the number of job postings requiring at least one "complementary", "substitutable", or "AI/ML" skill, as well as the total number of skills clusters that are mentioned.

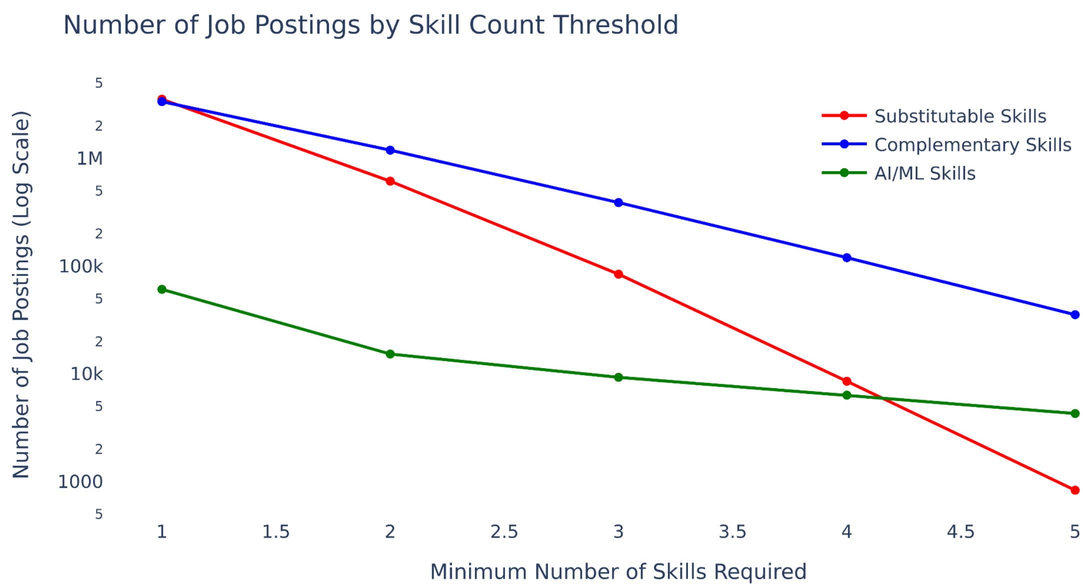

Figure S1. The Count of Job Postings requiring "Complementary", "Substitutable" or "Artificial Intelligence/Machine Learning" Skills. The graph further reveals how many individual skills clusters of each skill type are mentioned in job postings.

AI Skill (w/ >200 count)	Count	Included
Machine Learning	57774	False
Artificial Intelligence	46187	False
Deep Learning	8807	True
TensorFlow	6784	True
Automation Systems	6217	True
Text Retrieval Systems	5800	True
Data Version Control (DVC)	4705	True
Machine Learning Algorithms	4448	True
PyTorch (Machine Learning Library)	4350	True
Artificial Neural Networks	3382	True
Scikit-Learn (Python Package)	3249	True
Generative Artificial Intelligence	3015	True
Chatbot	2478	True
Keras (Neural Network Library)	2045	True
MLOps (Machine Learning Operations)	1571	True
AWS SageMaker	1505	True
Random Forest Algorithm	1273	True
Intelligent Automation	1192	True
Reinforcement Learning	1167	True
Feature Engineering	1088	True
Machine Learning Methods	1062	True
Systems Automation	1056	True
Support Vector Machine	1028	True
Automated Data Cleaning	959	True
Knowledge-Based Systems	923	True
Large Language Modeling	918	True
OpenCV	796	True
Natural Language Understanding (NLU)	768	True
Azure Machine Learning	767	True
Boosting	710	True
Unsupervised Learning	649	True
AIOps (Artificial Intelligence For IT Operations)	648	True
Recommender Systems	646	True
Cognitive Computing	616	True
Torch (Machine Learning)	610	True
H2O.ai	596	True
Transformer (Machine Learning Model)	550	True
Object Tracking	549	True
Apache MXNet	540	True
Dynamic Routing	533	True
Applications Of Artificial Intelligence	504	True
Knowledge Engineering	502	True
AI Research	501	True
Recurrent Neural Network (RNN)	488	True
OpenAI Gym Environments	476	True
Kubeflow	462	True
Association Rule Learning	455	True
Federated Learning	444	True
Feature Extraction	438	True
Data Sovereignty	426	True
Edge Intelligence	426	True
Language Models	425	True
Xgboost	421	True
MLflow	418	True
Theano (Software)	403	True
Feature Selection	395	True
Intelligent Systems	390	True
General-Purpose Computing On Graphics Processing Units	363	True
Knowledge-Based Configuration	349	True
Machine Learning Model Training	345	True
Expert Systems	343	True
Generative Adversarial Networks	325	True
Text to Speech (TTS)	324	True
Supervised Learning	322	True
ChatGPT	315	True
Gradient Boosting	308	True
Artificial Intelligence Development	307	True
Support Vector Machines (SVM)	306	True
Automated Machine Learning	295	True
Convolutional Neural Networks (CNN)	292	True
Distributed Machine Learning	288	True
Prompt Engineering	282	True
Dask (Software)	277	True
Knowledge Representation	273	True
Multi-Agent Systems	272	True
Artificial Intelligence Markup Language (AIML)	271	True
Apache Mahout	269	True
Concept Drift Detection	267	True
Intelligent Virtual Assistant	263	True
Bagging Techniques	259	True
Long Short-Term Memory (LSTM)	252	True
Ensemble Methods	251	True
AI/ML Inference	242	True
Transfer Learning	238	True
Deep Learning Methods	237	True
Voice Assistant Technology	232	True
ModelOps	206	True

Table S7. Skills Used to Identify AI-related Roles from Job Descriptions.
The set of skills is drawn from Lightcasts' "Artificial Intelligence and Machine Learning (AI/ML)" subcategory. "Machine Learning" and "Artificial Intelligence" are excluded from the set of skills used to construct the final sample of AI-related roles for the analysis. We further report the number of job descriptions mentioning each skill with at least 200 instances.

S3. Applied Methods

This section outlines the statistical models used to estimate internal and external effects, including logistic and linear regressions, as well as the control variables employed.

S3.A. Internal Effects Analysis

Regression as a method of analysis has an established precedent of being used to understand the relationships between artificial intelligence and patterns demand patterns in the labour market (e.g. 1, 40). In this paper, we analyse the internal effects by employing a logistic regression to understand the associations between AI roles and demand for complementary and substitutable skills. The set of control variables included in this regression analysis is provided in Table S8.

The regression formula is captured as follows:

$$\log(\frac{p}{1-p}) = \beta_0 + \beta_1 X_{1,i} + \delta \mathbf{X}_i' + \epsilon_i$$

Where:

- $p = Pr(Y_i = 1)$ is the probability of a job posting advertising a given "complementary" skill Y_i
- β_0 is the intercept
- β_1 captures the effect of a job posting being AI-related
- $X_{1,i} = 1$ indicates that job posting i is AI-related
- X_i' is a vector of control variables, as listed in Table S8

The complete set of results is presented in Table S9. We also provide results for the demand for "substitutable" skills in Table S10.

After this main analysis of the internal effects, we proceed to explore whether the demand for skills is reflected in the salaries paid in certain roles. We use a linear regression to understand how the presence of "complementary" or "substitutable" skills affect the (log-transformed) salary in AI-related roles. We again include the control variables listed in Table S8.

The regression formula for the wage analysis is written as:

$$\log(Y_i) = \beta_0 + \beta_1 X_{1,i} + \delta \mathbf{X}_i' + \epsilon_i$$

Where:

- $log(Y_i)$ is the salary (log-transformed) for a given role i
- β_0 is the intercept

- β_1 captures the effect of job-posting i requiring a given complementary or substitutable skill
- $X_{1,i} = 1$ if job-posting i requires a given complementary or substitutable skill
- X_i' is a vector of control variables, as listed in Table S8.

Tables S11 and S12 report the regression results for this wage analysis.

S3.B. External Effects

To investigate the effect of AI prevalence on the demand of “complementary” and “substitutable” skill in non-AI roles, we employ a fractional logistic model. We aggregate the job postings data by year and conduct analyses at the company, industry, and regional level. Thus, we are able to measure AI prevalence as the share of job postings within a given entity, which are classified as AI-related roles. The main external effects analysis is conducted on the sample of companies, industries, or regions with at least one AI-related job posting. A set of control variables is listed in Table S8.

The regression equation is expressed as follows:

$$\log\left(\frac{p}{1-p}\right) = \beta_0 + \beta_1 X_{1,i} + \delta \mathbf{X}_i' + \epsilon_i$$

Where:

- $p = E(y_{i,k}|X_{i,k})$ is the predicted share of Non-AI related job postings requiring “complementary” or “substitutable” skills in year i and company, industry, or region k
- $X_{1,i,k}$ captures AI penetration (share of job postings demanding AI skills) by year i and company, industry, or region level k
- β_0 is the intercept
- β_1 is the coefficient on AI prevalence. The sign of the coefficient indicates the direction of the effect of AI prevalence on demand for “complementary” or “substitutable” skills in non-AI roles ($Y_{i,k}$)
- $\epsilon_{i,k}$ is the error term

At the company-level, we observe an inflated number of companies with zero AI roles posted for all three geographies. This zero-inflation further allows us to extend our main analysis to the extensive margin. Hence, we can capture how the demand for “complementary” or “substitutable” skills is affected by whether or not the company has any AI-related postings. In this case, our regression equation presented above remains unchanged, except that our main explanatory variable is now expressed as follows:

$$X_{1,i,k} = \begin{cases} 1, & \text{company } k \text{ has} \geq 1 \text{ AI postings} \\ 0, & \text{company } k \text{ has } 0 \text{ AI postings} \end{cases}$$

The complete set of results, at the company, industry, and region levels for the United States, United Kingdom, Australia and New Zealand are presented in Tables S13. The extensive margin results at the company level are further displayed in Table S14.

Control Variable	**Description/Operationalisation**	**Justification**
Minimum years of experience *(internal effects)*	Minimum years of experience required. Discrete variable as specified by job posting.	Salary differs by experience level and different experience levels are associated with different skills demands (41, 42, 43)
Minimum education level *(internal effects)*	Minimum education level, as specified by job posting. (None listed, High School or GED, Associate's Degree, Bachelor's Degree, Master's Degree, PhD or professional degree) (ordinal variable)	Salaries differ by education level and skills demand is related to education levels (44, 4, 45, 46)
Year *(internal and external effects)*	Year (control variables for 2019-2023 included, reference year is the omitted category 2018)	Labour/skills demand and salary fluctuate and differ year to year (44, 45)
Region *(internal effects)*	Controlling for regional fixed effects.	
Industry *(internal and external effects at company-level)*	Controlling for industry-specific fixed effects.	
Total postings *(external effects)*	Total number of job postings per year per observation category (company, industry or region)	Captures overall labour market activity, ensuring that the observed effects of AI role postings are not confounded by broader variations in labour demand (e.g., market size fluctuations).

Table S8. List of Control Variables Included in the Internal and External Effects Regression Analyses. The choice of control variables is based on a literature review, as outlined in the third column.

S4. Results

S4.A. Descriptive Evidence

This section presents descriptive evidence of the demand for “complementary” and “substitutable” skills between 2018 and 2024. In the main manuscript, Figure 1 plots the odds-ratios for each of the seven “complementary” skills clusters over this time period. The graph reveals that five out of seven clusters are consistently more commonly demanded in AI-related roles, as opposed to non-AI roles. Here, Figure S2 replicates the odds-ratio calculations for the five “substitutable” skills clusters.

Motivated by recent findings (e.g., 49, 18) suggesting a recent major step change in AI adoption, specifically the use of (generative) AI to substitute and complement knowledge work, we further investigate the *change* in demand for complementary and substitutable skills clusters across AI role categories over time. The left panel of Figure S3 plots the share of AI-related and non-AI roles which require at least one of the skills clusters associated with the corresponding “complementary” or “substitutable” skills categories between 2018 and 2024. We further plot the median salaries associated with different skills categories and AI versus non-AI related roles in the right panel of the figure.

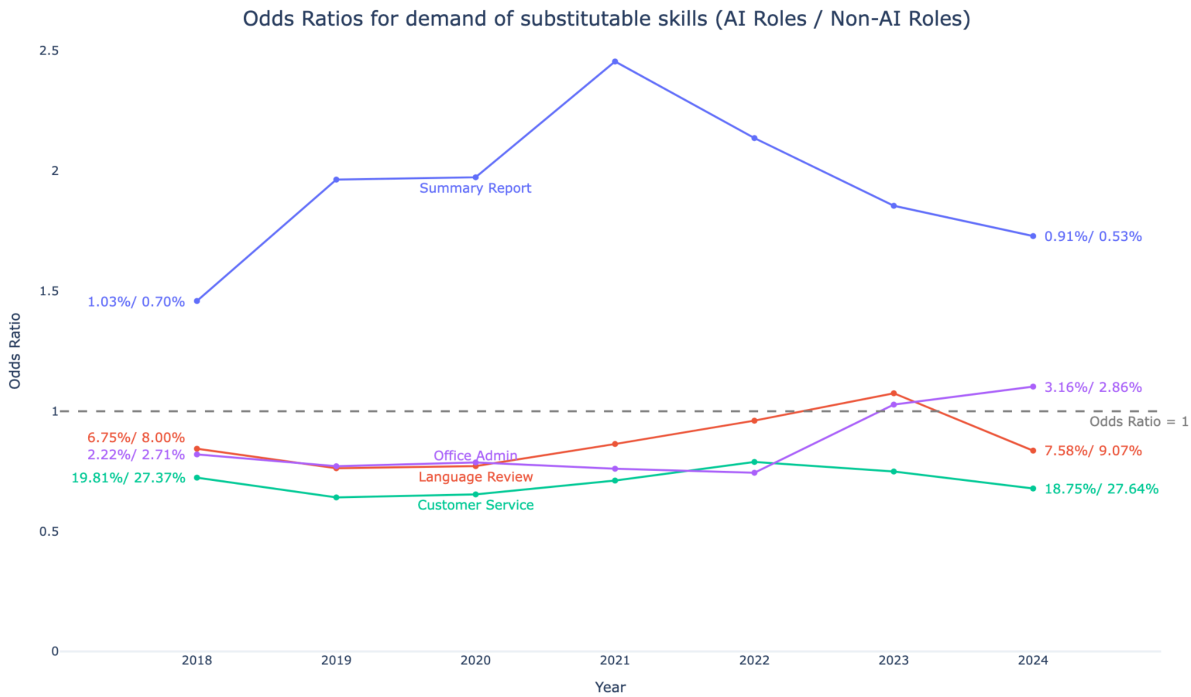

Figure S2. Calculated odds-ratios relating the demand for “substitutable” skills in AI-related vs non-AI roles. “Customer Service” skills are consistently less common in AI roles. “Language Review” and “Office Admin” skills are also less common in AI roles until the later years of the sample (2023-2024), where they become more commonly demanded in AI-related roles. Meanwhile, “summary report” skills are consistently higher demanded in AI-related roles than non-AI roles.

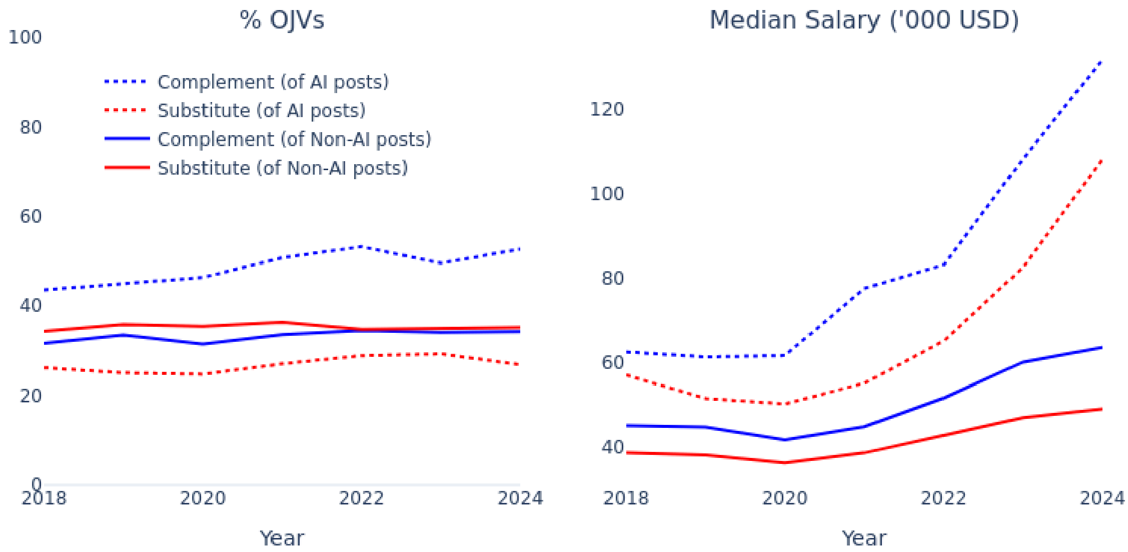

Figure S3. Skills demand and median salaries across job postings between 2018 and 2024. The left panel plots the demand for any "complementary" or "substitutable" skill in AI-related and non-AI roles. Demand for "complementary" skills is consistently higher than 40%, and growing between 2018 and 2024, while demand for "substitutable" skills remains between 20 and 30% amongst AI-related roles. In non-AI roles, "substitutable" skills are marginally more demanded than "complementary" skills, and the demand converges after 2022. The right panel plots the median salaries in job roles and reveals that while salaries are generally increasing, they are consistently highest in AI-related roles, specifically those demanding "complementary" skills. Median salaries are lowest and experience the least growth in non-AI roles, although those roles requiring "complementary" skills are again associated with higher salaries here.

S4.B. Internal Effects Results

In this section we provide results from the internal effects analysis, beyond the findings presented in Figure 2 in the main manuscript. First, we explore how working with AI technologies affects the demand for "substitutable" skills within roles. We then proceed to modelling monetary valuation of skills by running a linear regression to capture how skills requirements affect the salary paid in AI-related roles. The resulting coefficients are presented visually in Figures S4 and S5.

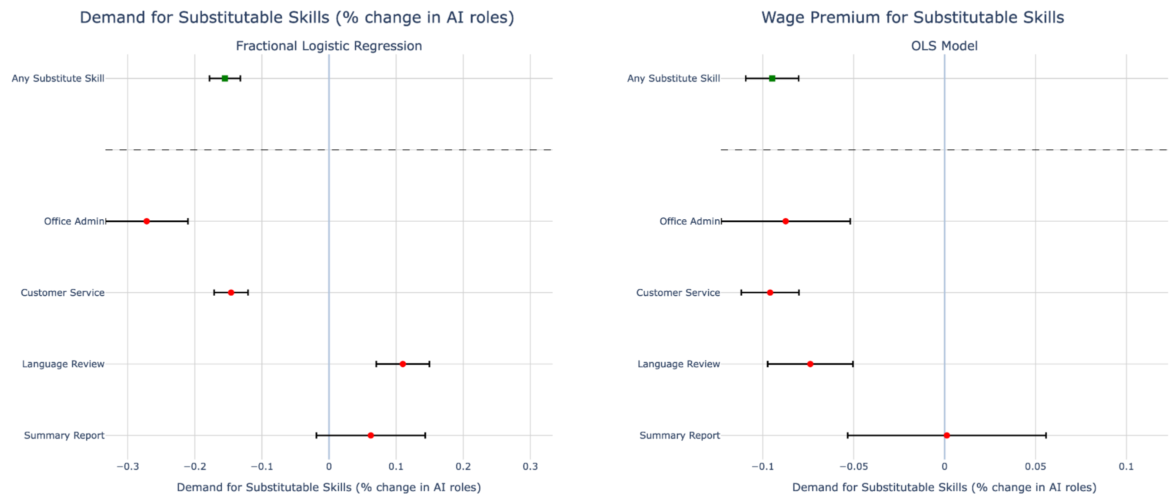

Figure S4. Visual Representation of Internal Effects Regression Results for "Substitutable" Skills. The left panel presents the effects of working with AI on the demand for "substitutable" skills. The right panel presents coefficients from linear regressions (OLS method) relating the presence of "substitutable" skills in AI-related roles to (log) salaries paid.

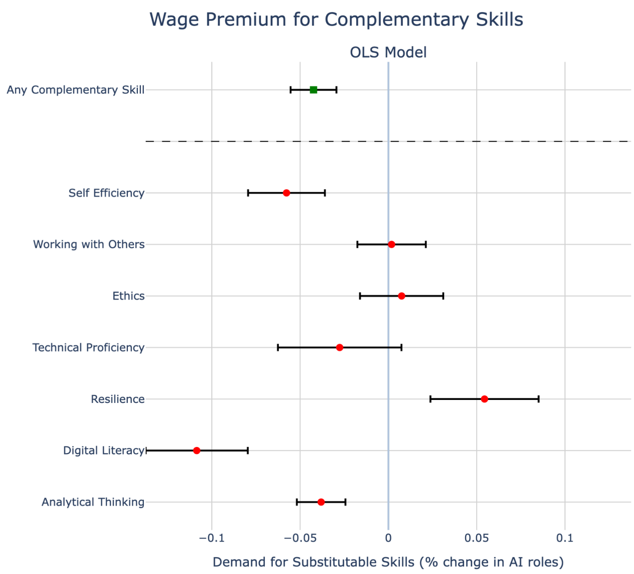

Figure S5. Visual Representation of Internal Effects Wage Regressions Results for "Complementary" Skills. Coefficients from linear regressions (OLS method) relating the presence of "complementary" skills in AI-related roles to (log) salaries paid.

We further provide the complete regression results for all internal effects analyses on "complementary" and "substitutable" skills. For "complementary" skills, as presented in Figure 2 of the main manuscript, the demand analysis is conducted for all occupations, as well as selected ONET occupation categories: management, business and financial operations, sales and related, and office and administrative support occupations. The complete results are displayed in Table S9.

Regression results for the wage premium analysis, and results for "substitutable" skills are further reported in Tables S10, S11, and S12.

As reported in Table S9 and Figure 2 in the main manuscript, the selection and extent of skills demanded further varies when selecting on occupations, particularly those where the potential for human-specific value added is expected to be rather high. We further explore this concept in Figure S6. Similar to Figure S2, this plots the odds-ratio for different “complementary” skills, although here we track how this relative demand changes with seniority of the job roles. There can be read a general increase in demand for “complementary” skills with years of experience. In positions demanding less experience, the majority of “complementary” skills clusters are more frequently demanded in AI-related than non-AI roles, though this difference drastically diminishes in more senior positions. The figure further compares salaries paid to roles with or without the given “complementary” skills, though no clear pattern can be identified here.

Figure S6. Tracking changes in demand for “complementary” skills with seniority levels of roles. The upper panel plots the odds ratio of demand for skills in AI-related versus non-AI roles across different experience levels. Overall, the difference in demand for “complementary” skills between roles working directly with or without AI technologies diminishes with seniority. The lower panel displays the ratio in salaries paid for different levels of experience, contrasting roles requiring a given “complementary” skill with ones that do not.

Dependent variables:	Analytical Thinking	Digital Literacy	Resilience	Technical Proficiency	Ethics	Working with Others	Self Efficiency	Any Complementary Skill
All Occupations								
AI	0.17***	-0.00	0.11***	0.24***	-0.02	0.11***	0.22***	0.18***
	(0.01)	(0.02)	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.01)
Years of Experience (min)	0.03***	-0.04***	0.05***	0.03***	0.04***	0.05***	-0.00***	0.03***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Intercept	-1.82***	-2.05***	-3.99***	-3.39***	-2.82***	-2.67***	-3.07***	-0.66***
	(0.02)	(0.02)	(0.04)	(0.04)	(0.02)	(0.02)	(0.03)	(0.01)
Fixed Effects:								
Minimum education level	✓	✓	✓	✓	✓	✓	✓	✓
Year	✓	✓	✓	✓	✓	✓	✓	✓
Region	✓	✓	✓	✓	✓	✓	✓	✓
Industry	✓	✓	✓	✓	✓	✓	✓	✓
Occupation	✓	✓	✓	✓	✓	✓	✓	✓
N	4520774	4520774	4520774	4520774	4520774	4520774	4520774	4520774
Pseudo R^2	0.063	0.055	0.034	0.079	0.043	0.031	0.029	0.051
Management (ONET 11)								
AI	0.32***	0.15***	0.12*	0.42***	-0.10**	0.20***	0.28***	0.28***
	(0.03)	(0.06)	(0.07)	(0.09)	(0.05)	(0.04)	(0.05)	(0.03)
Years of Experience (min)	0.04***	-0.08***	0.03***	0.02***	0.04***	0.05***	-0.01***	0.03***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Intercept	-1.79***	-1.48***	-3.89***	-4.25***	-2.07***	-2.41***	-3.13***	-0.51***
	(0.04)	(0.05)	(0.08)	(0.12)	(0.05)	(0.05)	(0.06)	(0.03)
Fixed Effects:								
Minimum education level	✓	✓	✓	✓	✓	✓	✓	✓
Year	✓	✓	✓	✓	✓	✓	✓	✓
Region	✓	✓	✓	✓	✓	✓	✓	✓
Industry	✓	✓	✓	✓	✓	✓	✓	✓
Occupation	✗	✗	✗	✗	✗	✗	✗	✗
N	616251	616251	616251	616251	616251	616251	616251	616251
Pseudo R^2	0.026	0.040	0.015	0.017	0.011	0.015	0.012	0.018
Business & Financial Operations (ONET 13)								
AI	0.15***	-0.19***	-0.19**	0.32***	-0.05	0.26***	0.15***	0.14***
	(0.03)	(0.07)	(0.09)	(0.10)	(0.05)	(0.05)	(0.05)	(0.03)
Years of Experience (min)	0.01***	-0.08***	0.04***	0.05***	0.05***	0.05***	-0.03***	0.01***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Intercept	-1.10***	-1.41***	-3.35***	-3.23***	-2.75***	-2.36***	-2.15***	-0.06
	(0.05)	(0.07)	(0.12)	(0.14)	(0.08)	(0.07)	(0.07)	(0.04)
Fixed Effects:								
Minimum education level	✓	✓	✓	✓	✓	✓	✓	✓
Year	✓	✓	✓	✓	✓	✓	✓	✓
Region	✓	✓	✓	✓	✓	✓	✓	✓
Industry	✓	✓	✓	✓	✓	✓	✓	✓
Occupation	✗	✗	✗	✗	✗	✗	✗	✗
N	478266	478266	478266	478266	478266	478266	478266	478266
Pseudo R^2	0.020	0.029	0.017	0.015	0.017	0.016	0.008	0.018
Sales & Related (ONET 41)								
AI	0.83***	-0.11	-0.33**	0.22	0.34***	-0.19**	0.99***	0.76***
	(0.06)	(0.10)	(0.16)	(0.15)	(0.08)	(0.10)	(0.06)	(0.06)
Years of Experience (min)	0.09***	-0.06***	-0.01**	0.06***	0.02***	0.07***	-0.01***	0.05***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Intercept	-2.08***	-1.85***	-3.74***	-4.61***	-1.39***	-2.73***	-3.24***	-0.34***
	(0.05)	(0.06)	(0.10)	(0.17)	(0.06)	(0.07)	(0.08)	(0.04)
Fixed Effects:								
Minimum education level	✓	✓	✓	✓	✓	✓	✓	✓
Year	✓	✓	✓	✓	✓	✓	✓	✓
Region	✓	✓	✓	✓	✓	✓	✓	✓
Industry	✓	✓	✓	✓	✓	✓	✓	✓
Occupation	✗	✗	✗	✗	✗	✗	✗	✗
N	388744	388744	388744	388744	388744	388744	388744	388744
Pseudo R^2	0.049	0.031	0.022	0.044	0.040	0.019	0.029	0.021
Office & Administration Support (ONET 43)								
AI	1.06***	-0.18**	0.07	0.17	0.01	0.28***	1.63***	0.88***
	(0.05)	(0.08)	(0.12)	(0.19)	(0.10)	(0.09)	(0.06)	(0.06)
Years of Experience (min)	0.08***	-0.05***	0.08***	0.05***	0.07***	0.10***	0.04***	0.07***
	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)
Intercept	-1.78***	-1.70***	-3.25***	-5.53***	-2.80***	-2.26***	-3.21***	-0.53***
	(0.05)	(0.05)	(0.10)	(0.20)	(0.08)	(0.07)	(0.08)	(0.04)
Fixed Effects:								
Minimum education level	✓	✓	✓	✓	✓	✓	✓	✓
Year	✓	✓	✓	✓	✓	✓	✓	✓
Region	✓	✓	✓	✓	✓	✓	✓	✓
Industry	✓	✓	✓	✓	✓	✓	✓	✓
Occupation	✗	✗	✗	✗	✗	✗	✗	✗
N	409570	409570	409570	409570	409570	409570	409570	409570
Pseudo R^2	0.034	0.021	0.036	0.016	0.025	0.031	0.015	0.023

Standard errors in parentheses. * $p<0.1$, ** $p<0.05$, *** $p<0.01$

Table S9. Regression Results for “Complementary” Skills Demand. Results from logistic regressions capturing the effect of working with AI technologies (AI-related roles) on demand for “complementary” skills. The analysis is performed on the complete sample of job postings, as well as subsamples of management, business and finance, sales, and office and administrative support occupations.

Dependent variables:	Summary Report	Language Review	Customer Service	Office Admin	Any Substitutable Skill
			All Occupations		
AI	0.06	0.11***	-0.15***	-0.27***	-0.16***
	(0.04)	(0.02)	(0.01)	(0.03)	(0.01)
Years of Experience (min)	0.03***	-0.05***	-0.04***	0.04***	-0.04***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Intercept	-5.59***	-2.80***	-0.95***	-4.87***	-0.82***
	(0.07)	(0.02)	(0.02)	(0.04)	(0.01)
Fixed Effects:					
Minimum education level	✓	✓	✓	✓	✓
Year	✓	✓	✓	✓	✓
Region	✓	✓	✓	✓	✓
Industry	✓	✓	✓	✓	✓
Occupation	✓	✓	✓	✓	✓
N	4520774	4520774	4520774	4520774	4520774
Pseudo R^2	0.086	0.050	0.123	0.138	0.105

Standard errors in parentheses. * p<0.1, ** p<0.05, ***p<0.01

Table S10. Regression Results for "Substitutable" Skills Demand. Results from logistic regressions capturing the effect of working with AI technologies (AI-related roles) on demand for "substitutable" skills.

Dependent variable: Salary (log)

Skills premium for:	Analytical Thinking	Digital Literacy	Resilience	Technical Proficiency	Ethics	Working with Others	Self Efficiency	Any Complementary Skill
				All Occupations				
Skill's premium	-0.04***	-0.11***	0.05***	-0.03	0.01	0.00	-0.06***	-0.04***
	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
Years of Experience (min)	0.10***	0.10***	0.10***	0.10***	0.10***	0.10***	0.10***	0.10***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Intercept	10.75***	10.76***	10.74***	10.75***	10.74***	10.74***	10.74***	10.76***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Fixed Effects:								
Minimum education level	✓	✓	✓	✓	✓	✓	✓	✓
Year	✓	✓	✓	✓	✓	✓	✓	✓
Region	✓	✓	✓	✓	✓	✓	✓	✓
Industry	✓	✓	✓	✓	✓	✓	✓	✓
Occupation	✓	✓	✓	✓	✓	✓	✓	✓
R-squared	0.67	0.67	0.67	0.67	0.67	0.67	0.67	0.67
R-squared Adj.	0.67	0.67	0.67	0.67	0.67	0.67	0.67	0.67
N	9990	9990	9990	9990	9990	9990	9990	9990

Standard errors in parentheses. * p<0.1, ** p<0.05, ***p<0.01

Table S11. Regression Results for Wage Effects for "Complementary" Skills. Results from linear regressions relating the requirement for "complementary" skills to wages offered within AI-related roles.

Dependent variable: Salary (log)

Skills premium for:	Summary Report	Language Review	Customer Service	Office Admin	Any Substitutable Skill
			All Occupations		
Skill's premium	0.00	-0.07***	-0.10***	-0.09***	-0.09***
	(0.03)	(0.01)	(0.01)	(0.02)	(0.01)
Years of Experience (min)	0.10***	0.10***	0.10***	0.10***	0.10***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Intercept	10.74***	10.75***	10.77***	10.74***	10.78***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Fixed Effects:					
Minimum education level	✓	✓	✓	✓	✓
Year	✓	✓	✓	✓	✓
Region	✓	✓	✓	✓	✓
Industry	✓	✓	✓	✓	✓
Occupation	✓	✓	✓	✓	✓
R-squared	0.67	0.67	0.67	0.67	0.68
R-squared Adj.	0.67	0.67	0.67	0.67	0.67
N	9990	9990	9990	9990	9990

Standard errors in parentheses. * p<0.1, ** p<0.05, ***p<0.01

Table S12. Regression Results for Wage Effects for "Substitutable" Skills. Results from linear regressions relating the requirement for "substitutable" skills to wages offered within AI-related roles.

S4.C. External Effects Results

This section presents additional results from the external effects analysis, which investigates the relationship between AI prevalence and skills demanded in non-AI roles. This material provides further details regarding the results displayed in Figure 3 in the main manuscript. Figures S6 and S7 plot the relationship between AI prevalence and “complementary” or “substitutable” skills in non-AI jobs at the company, industry, and region level, for the United Kingdom, and Australia and New Zealand. As in Figure 3, the graphs reveal changing trends between the earlier and later years of our sample (2018-2019 versus 2023-2024). A positive relationship between AI prevalence and demand for “complementary” skills in non-AI roles can be observed at the company, industry, region levels both for the United Kingdom, and Australia and New Zealand. With the exception of the United Kingdom’s industry level, this relationship is stronger in the later years (2023-2024) of the sample. For “substitutable” skills, demand in non-AI roles varies between slightly increasing, to decreasing, to no significant relationship, depending on the level, geography, and year of the analysis.

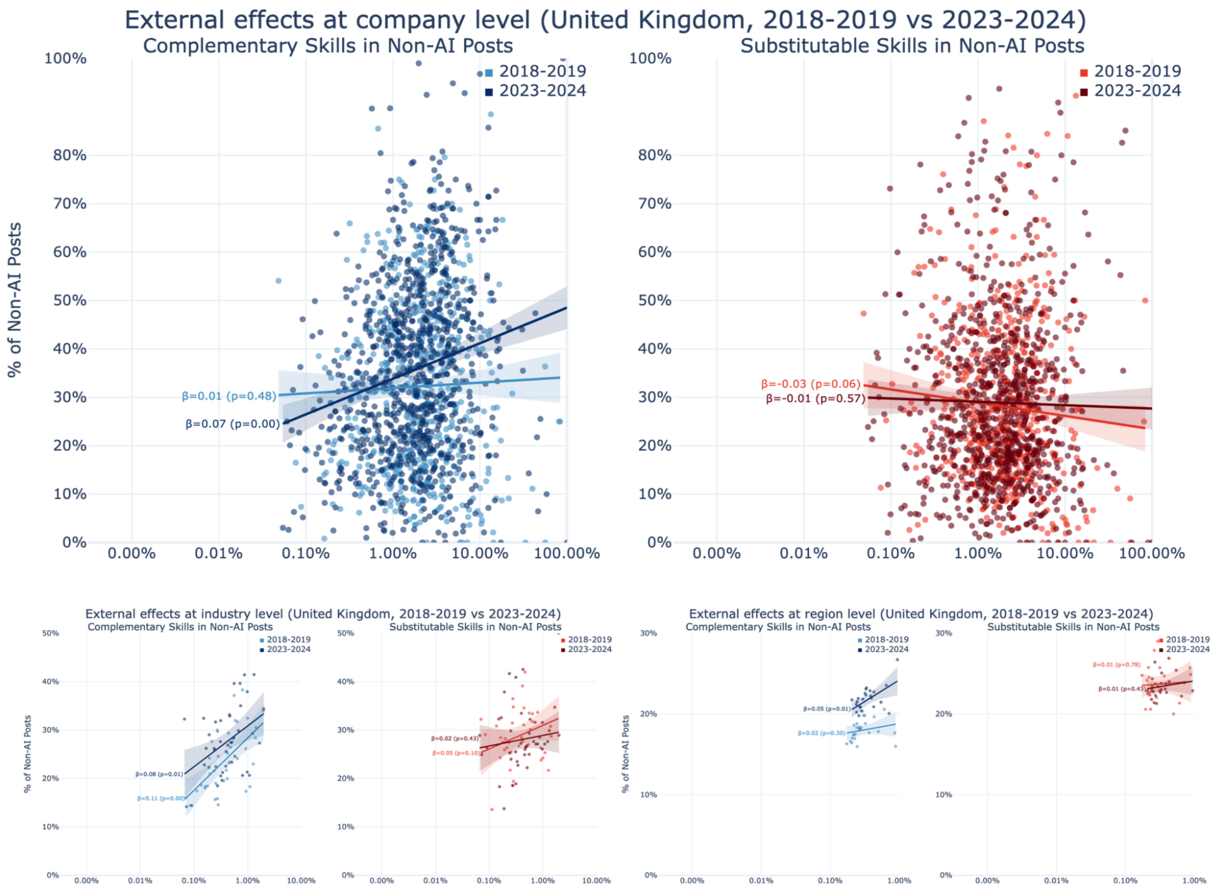

Figure S7. Descriptive Evidence of External Effects for the United Kingdom, 2018-2024 at the Company, Industry, and Region Level. The scatterplots reveal the relationship between AI prevalence (the share of AI-related roles) within an entity, and the demand for “complementary” or “substitutable” skills in non-AI roles. For “complementary” skills, a positive relationship can be observed, which appears stronger in the later years (2023-2024) of the sample. For “substitutable” skills, a slight negative relationship can only be read at the company level.

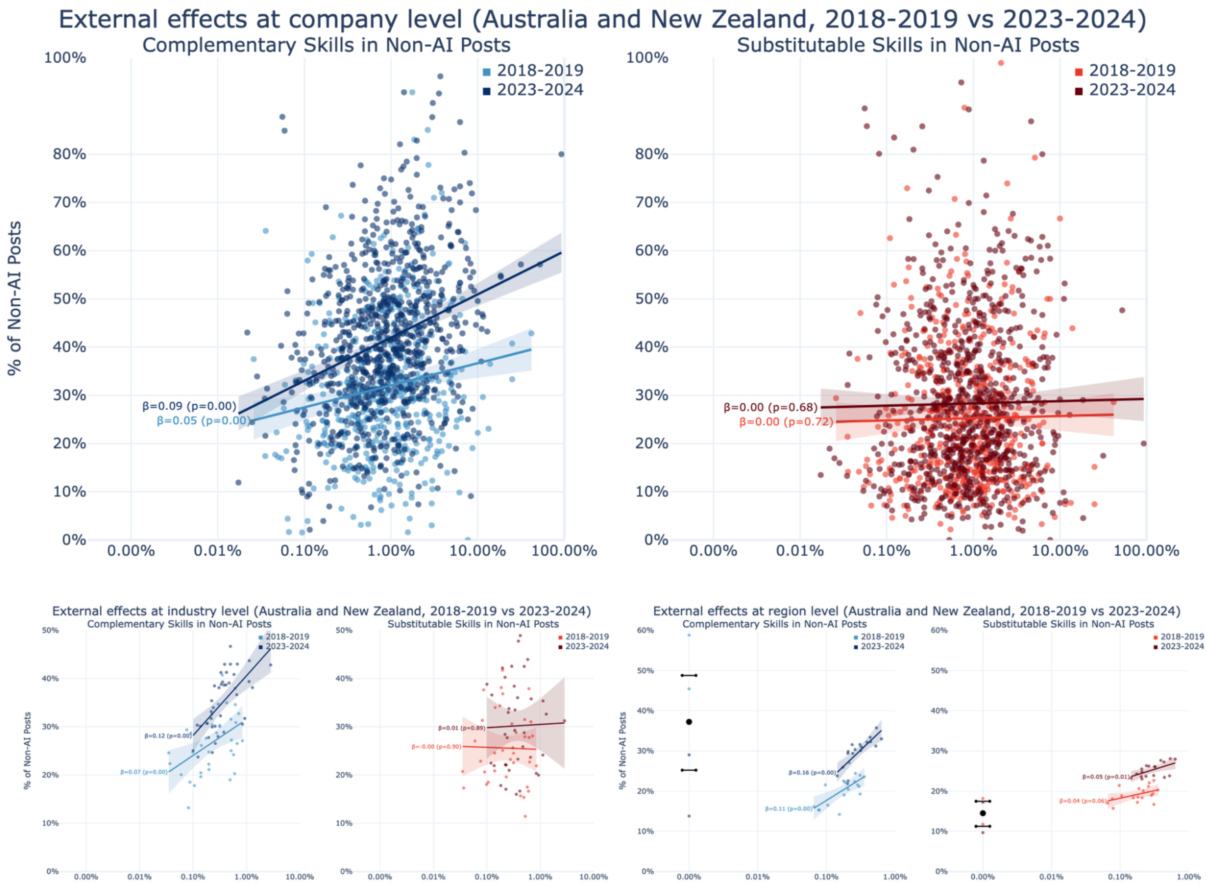

Figure S8. Descriptive Evidence of External Effects for Australia and New Zealand, 2018-2024 at the Company, Industry, and Region Level. The scatterplots reveal the relationship between AI prevalence (the share of AI-related roles) within an entity, and the demand for “complementary” or “substitutable” skills in non-AI roles. For “complementary” skills, a positive relationship can be observed, which appears stronger in the later years (2023-2024) of the sample. For “substitutable” skills, the later years bring an upwards shift in skills demand within non-AI roles.

Building on to the simple evidence depicted in Figures S6, S7, as well as the scatter plots in Figure 3, a fractional logistic regression is employed to capture the effect of AI prevalence on skills demand in non-AI roles, including a set of controls and fixed effects as described in section S3. The complete results, as well as the calculated marginal effects, previously presented in the lower panel of Figure 3, are reported in Table S13.

It is particularly notable that Australia and New Zealand exhibit strong marginal effects of AI prevalence at the regional level. A 1 percentage point increase in AI prevalence within a region is here associated with a 18.23 percentage point increase in the demand for “complementary” skills in non-AI roles. By contrast, the marginal effects in the United States and the United Kingdom are 4.46 and 1.25 percentage points respectively. To understand the data composition leading to this interesting result, we plot the relationship between AI prevalence and demand for skills on a linear axis in Figure S8, with different colours distinguishing between different regions. This aims to reveal how each region contributes to the effect captured by our regression analysis. Among inspection of the graphs, the positive relationship between AI prevalence and “complementary” skills in non-AI jobs is particularly pronounced for Australia and New Zealand. It can further be observed that regions change values over the years and do not stick around the same points, so it appears unlikely that a few select regions are driving the regression results reported and calculated in Table S13.

	United States		United Kingdom		Australia & New Zealand	
Dependent variables:	**Complementary Skills**	**Substitutable Skills**	**Complementary Skills**	**Substitutable Skills**	**Complementary Skills**	**Substitutable Skills**
			— Company Level —			
AI prevalence (share AI-related roles)	2.35***	-3.63***	3.48***	-0.85	7.23***	-1.61
	(0.55)	(0.65)	(0.87)	(1.03)	(1.26)	(1.54)
Intercept	-0.60***	-0.13	-1.37***	-0.69***	-0.69***	-0.39***
	(0.10)	(0.11)	(0.18)	(0.19)	(0.13)	(0.14)
AI Marginal Effects (calculated)	0.57%	-0.81%	0.75%	-0.17%	1.66%	-0.31%
Fixed Effects:						
Year	✓	✓	✓	✓	✓	✓
Industry	✓	✓	✓	✓	✓	✓
N	6469	6469	2545	2545	2243	2243
AIC	6187.94	5918.58	2276.75	2199.23	2059.05	1873.95
			— Industry Level —			
AI prevalence (share AI-related roles)	47.06***	-15.89**	31.98***	6.81	37.89***	3.68
	(4.82)	(6.89)	(5.87)	(5.02)	(6.92)	(11.48)
Intercept	-0.16	-0.44	-0.68***	-0.46***	-0.25	0.42
	(0.15)	(0.27)	(0.17)	(0.14)	(0.20)	(0.26)
AI Marginal Effects (calculated)	10.77%	-3.74%	6.08%	1.38%	7.94%	0.74%
Fixed Effects:						
Year	✓	✓	✓	✓	✓	✓
Industry	✓	✓	✓	✓	✓	✓
N	138	138	140	140	130	130
AIC	137.08	140.35	125.85	129.99	124.12	122.15
			— Region Level —			
AI prevalence (share AI-related roles)	20.23***	-6.65***	7.90	6.89	99.88***	23.13**
	(2.45)	(2.52)	(5.67)	(4.21)	(10.86)	(9.26)
Intercept	-1.03***	-0.79***	-1.95***	-0.10	-2.28***	-1.93***
	(0.05)	(0.05)	(0.17)	(0.17)	(0.14)	(0.11)
AI Marginal Effects (calculated)	4.46%	-1.51%	1.25%	1.24%	18.23%	3.96%
Fixed Effects:						
Year	✓	✓	✓	✓	✓	✓
Industry	✓	✓	✓	✓	✓	✓
N	353	353	83	83	62	62
AIC	314.01	319.81	74.61	79.49	64.17	62.39

Standard errors in parentheses. * $p<0.1$, ** $p<0.05$, *** $p<0.01$

Table S13. Regression Results for External Effects Analysis. Results from fractional logistic regressions capturing how AI prevalence affects demand for “complementary” and “substitutable” skills in non-AI roles within companies, industries, and regions. The analysis is conducted for the United States, the United Kingdom, and Australia and New Zealand. The marginal effects of AI prevalence on skills demand are calculated and reported as well.

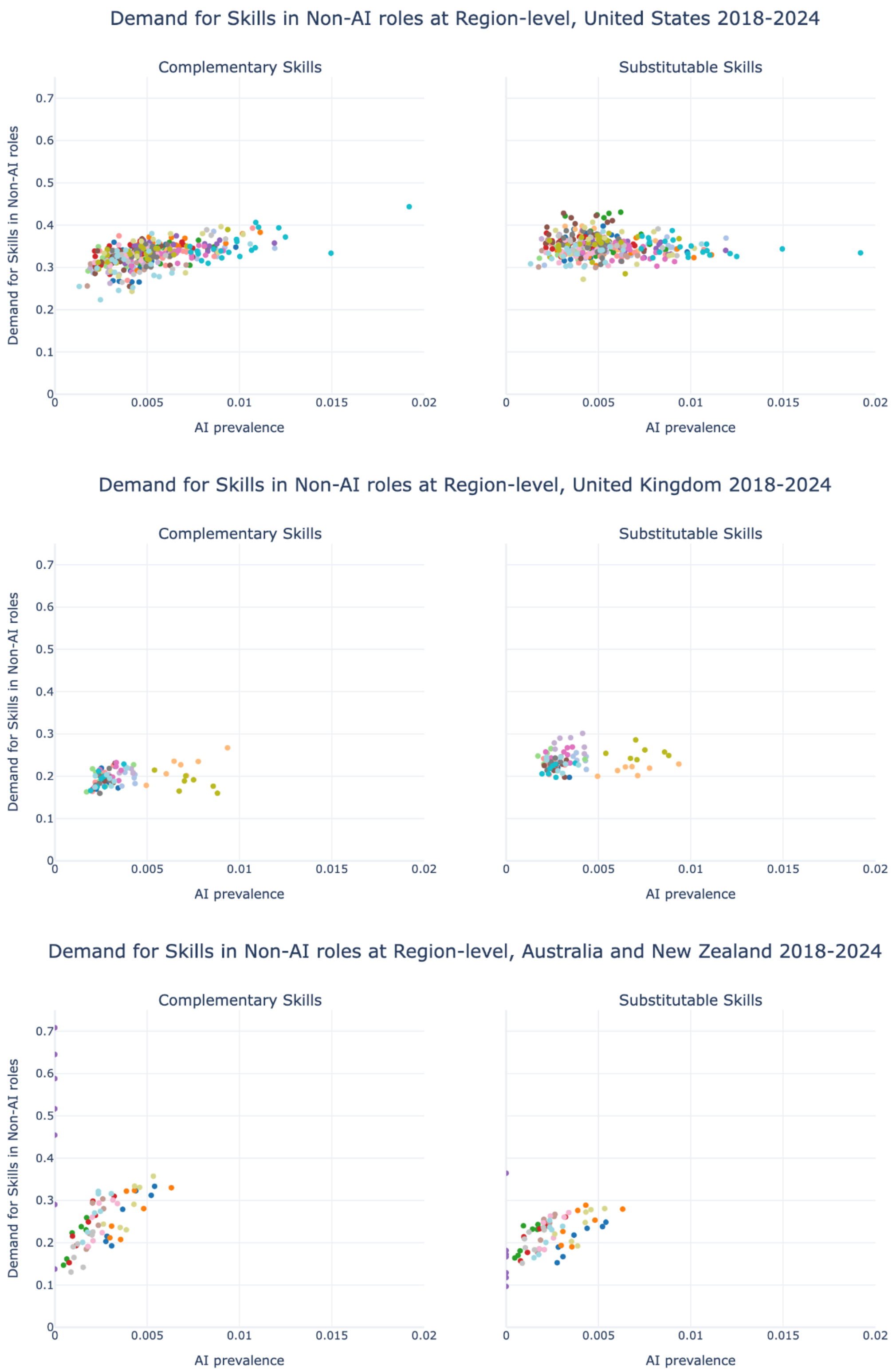

Figure S9. Skills Demand and AI Prevalence at the Region Level between 2018-2024 for the United States, the United Kingdom, Australia and New Zealand. The scatter plots reveal the positions of different regions for each geography to understand whether the external effects results are driven by patterns within or across different regions. Each datapoint represents a region-year pair.

We proceed to investigate how the selected skills clusters contribute to the overall effects captured for complementary or substitutable skills. First, we conduct the internal and external analyses outlined in sections S3.A and S3.B on 30 random skills subsamples, each using 75% of skills. Figure S10 visualises the distributions of coefficients resulting from the exercise. To understand how each individual skill contributes to the overall effect documented for 'complementary' or 'substitutable' skill, we measure the impact of any given skill on the coefficients. The results are presented in Figure S11. The external effects of decreased demand for 'substitutable' skills in non-AI roles are largely driven by the decreased demand for 'Customer Service' and 'Customer Support' skills. As AI-related roles become more common within companies, industries, and regions, such customer service related skills are demanded less frequently. A similar pattern can be observed in the internal effects analysis. For the external effects on 'complementary' skills, the positive demand effect is most commonly associated with the 'Problem-Solving' and 'Analytical Thinking' skills.

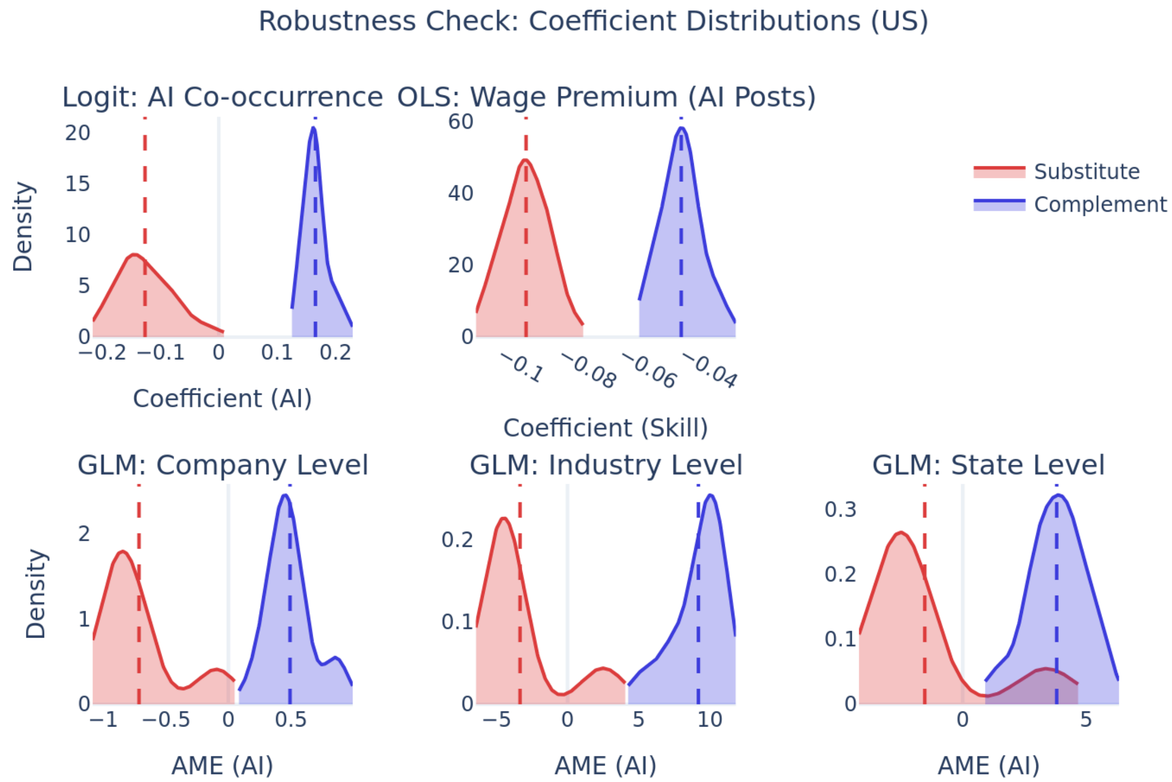

Figure S10. Density plots reporting the distributions of coefficients found for internal and external effects analyses when randomly varying the skills used to define 'complementary' and 'substitutable' skills. The upper panel reports coefficients from the internal effects analysis outlined in section S3.A, while the lower panel reports coefficients from the external effects analysis described in section S3.B.

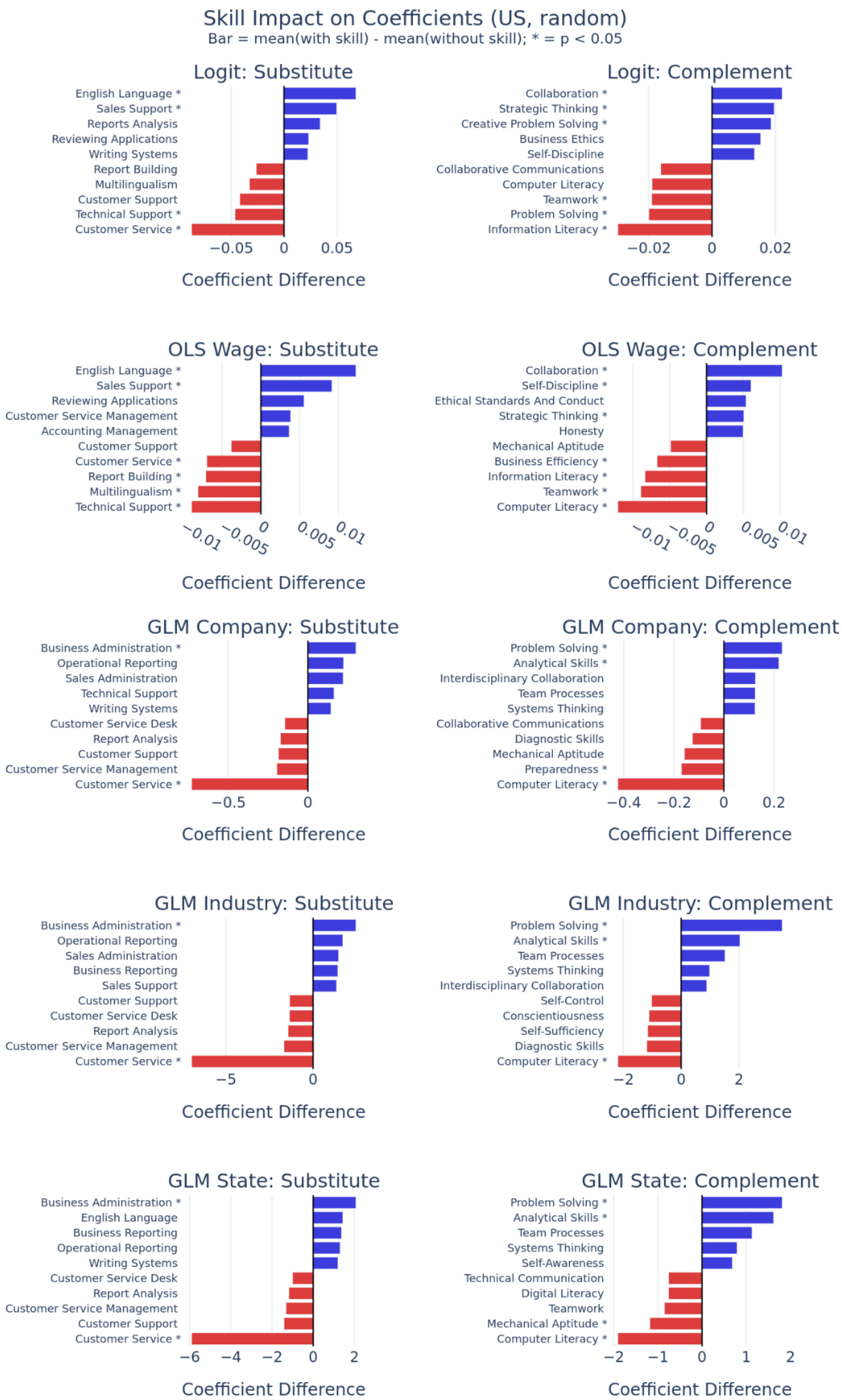

Figure S11. Contribution of individual skills cluster to the Internal and External Effects Results. The bar graphs plot the difference in coefficients reported for the analysis with and without each given skill. This exercise reveals how each skills cluster contributes to the overall effect reported for the demand of 'complementary' and 'substitutable' skills.

To verify the robustness of the external effects documented, we repeat our analysis for substitutable skills, omitting “Customer Service” skills, which, as shown in Figure S11, are the main contributors to the decreased demand effect observed. Figure S12 shows that, without “Customer Service” skills, only a very small negative relationship between AI prevalence and substitutable skills can be traced in our data of firms in the United States.

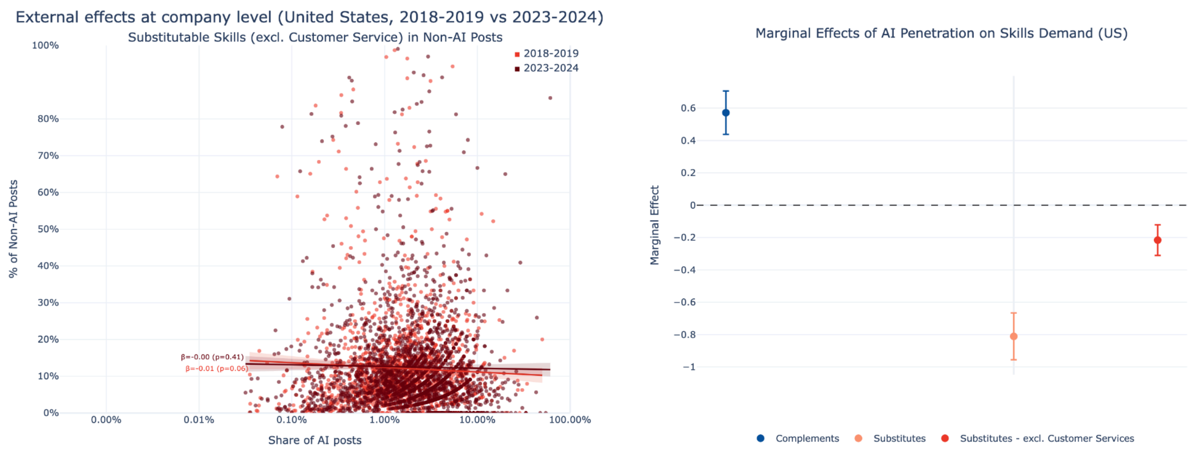

Figure S12. Robustness check of external effects results, excluding “Customer Service” skills from the set of substitutable skills. The scatter plot in the left panel relates the share of AI posts within a firm to the percentage of non-AI roles that require substitutable skills. The coefficients plotted in the right panel report a weaker negative relationship between AI prevalence and demand for substitutable skills, when “Customer Service” skills are excluded from the analysis.

We further present the results from the extensive margin analysis, investigating how AI presence, rather than AI prevalence, affects skills demanded in non-AI roles. As outlined in section S3.B, this analysis was performed at the company level, where AI presence is captured by a dummy variable indicating whether the given company has at least one AI-related role. The results reported in Table S14 indicate positive effects on demand for “complementary” skills and negative effects for “substitutable” skills. To illustrate, in the United States, a company with at least one AI-related role is associated with a 5.93 percentage point higher demand for “complementary” skills in its non-AI roles than a company that advertises no AI-related roles. For “substitutable” skills this demand difference lies at -2.64 percentage points.

	United States		United Kingdom		Australia & New Zealand	
Dependent variables:	**Complementary Skills**	**Substitutable Skills**	**Complementary Skills**	**Substitutable Skills**	**Complementary Skills**	**Substitutable Skills**
			— Company Level —			
AI (yes/no)	0.25***	-0.12***	3.48***	-0.85	0.28***	-0.04*
	(0.01)	(0.01)	(0.87)	(1.03)	(0.02)	(0.02)
Intercept	-0.85***	-0.39***	-1.37***	-0.69***	-0.81***	-0.65***
	(0.04)	(0.04)	(0.18)	(0.19)	(0.07)	(0.07)
AI Marginal Effects (calculated)	5.93%	-2.64%	0.75%	-0.17%	5.97%	-0.82%
Fixed Effects:						
Year	✓	✓	✓	✓	✓	✓
Industry	✓	✓	✓	✓	✓	✓
N	27831	27831	12956	12956	9625	9625
AIC	26751.48	26519.80	10703.74	11385.43	8558.87	8120.49

Standard errors in parentheses. * p<0.1, ** p<0.05, ***p<0.01

Table S14. Regression Results for External Effects Analysis, Extensive Margin. Results from fractional logistic regressions capturing how the presence of at least 1 AI-related role within a company affects demand for “complementary” and “substitutable” skills in non-AI roles. The analysis is conducted for the United States, the United Kingdom, and Australia and New Zealand. The marginal effects of AI presence on skills demand are calculated and reported as well.

S5. Compositional Analysis

The qualitative results of the internal effects analysis are robust to many specifications of the model with various different controls listed in Table S8. The one exception is when we control for the number of skills per post. Adding this control decreases the AI role coefficients for both “substitutable” and “complementary” skill demand. In particular, it makes the “complementary” skills coefficient negative, which changes the qualitative results. However, we find that adding this control always pushes down the relationship between any two groups of skills. The plots in Figure S13 relate “complementary” and “substitutable” skills with each other and a random sample of skills. When including the "SKILL_COUNT" control, the coefficients are always pushed downwards.

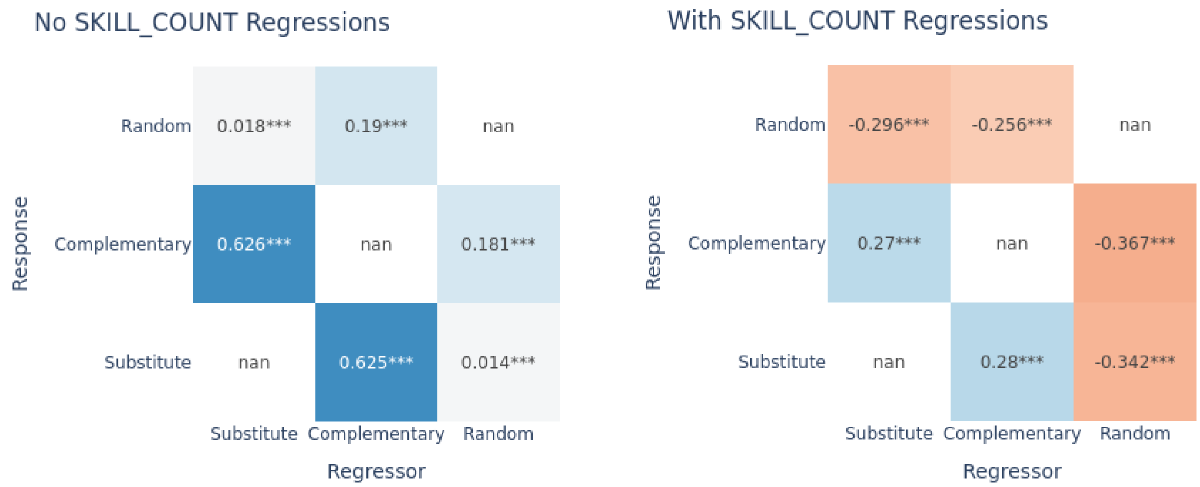

Figure S13. Relating complementary and substitutable skills with each other and a random sample of skills. The left panel does not control for the number of skills per job posting while the right panel does. All coefficients decrease when the number of skills is controlled for.

Hence, including the "SKILL_COUNT" control may induce a compositional effect whereby vacancies with the same number of skills must tradeoff which skills they have (e.g. one more AI skill means one less potential “substitutable” skill). In a compositional data structure, out-of-the-box regression methods cannot be applied due to the structural tradeoff in a composition. Therefore, we treat the AI and “complementary” or “substitutable” skills in a compositional analysis. This is useful if we assume that there is some type of skill requirement "budget" that job posts must consider when deciding which skill requirements to include in a post. To add one more AI skill means one less “substitutable” skill. In this setting, the presence of any distinct set of skills will tend to be negatively correlated with each other due to this tradeoff effect. The ternary plot in Figure S14 captures the distribution of AI job postings across the skills compositions. Apart from the majority of skills posted falling into the “other” category, the plots present descriptive evidence that “complementary” skills tend to coincide with AI skills more than “substitutable” skills do.

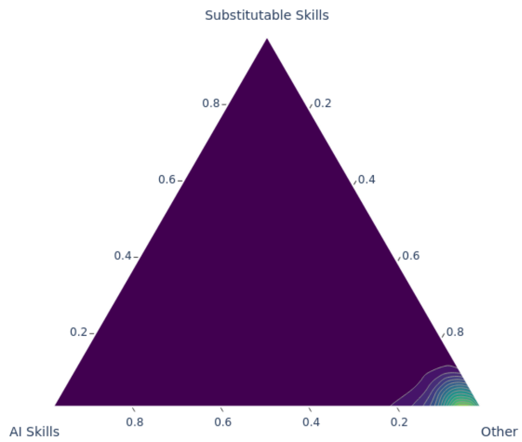

Fig. S14. Ternary plots mapping the distribution of job postings across skills compositions. The skills category “Other” refers to the complement of AI skills + “substitutable” skills, or AI skills + “complementary” skills, respectively. “Complementary” skills appear more likely to coincide with AI skills.

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