



Data for Impact

Data Primer

Summer 2024

Sections

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As part of LinkedIn’s vision to generate economic opportunity for all, Data for Impact seeks to:



Amplify the impact of public investments in economic and workforce development



Inform public policy decisions on digital and economic development strategy



Enable cutting-edge research on efforts to improve labor markets and economies



Labor Market Indicators

As of Summer 2024, LinkedIn offers 7 indicators on hiring, careers, and skills, which can be cut by up to 5 dimensions

Indicators

Indicator	Sample Description
LinkedIn Hiring Rate	Measure of hiring intensity
Female Representation	Share of labor market segment that is female
Career Transitions	Share of job changes to or from a specific industry or occupation
Reallocation Radar	Predictor of future cross-industry job transitions based on applications
Concentration	Share of labor market segment with specific skills or titles
Skills Genome	Most representative skills for each labor market segment

Skills Penetration

Share of representative skills that come from a specific group of skills

In some cases, data on migration, job postings, and remote jobs is available upon request

Dimensions

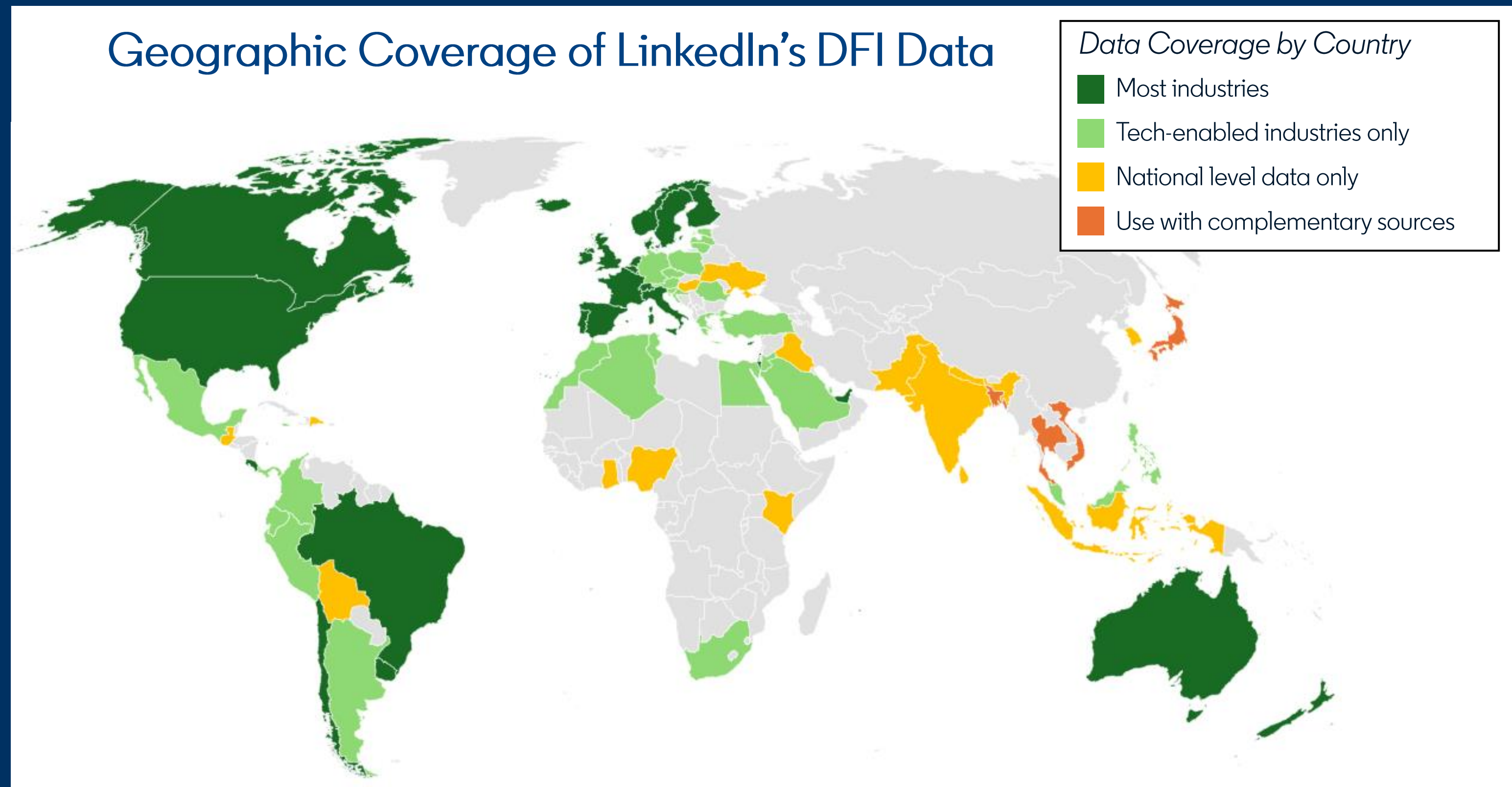
Not all dimensional cuts are available for all indicators

 National	Subnational cuts only available for Germany, India, US, and UK for some indicators.
 Industry	LinkedIn’s 20-industry taxonomy does not align to ISIC, and not all indicators are available for all industries.
 Skill Groups	LinkedIn’s skills taxonomy includes 40k+ skills, but analysis at this level is not possible. We can provide data at the level of skills groups, which include tech, disruptive tech, AI, green, soft, and business skills.
 Gender	We infer members’ gender through pronouns or first names; for this reason, gender data is not available in all geographies. We recognize that some LinkedIn members identify beyond traditional gender constructs.
 Occupational	LinkedIn’s occupational taxonomy includes thousands of occupations, though the exact number present depends on the geography. It does not align with ISCO, though partners have created crosswalks.

Geographic Coverage

Data across 78 countries

- The World Bank has validated use of LinkedIn data across 78 countries¹, but representativeness does vary. This map serves as a guide to inform data use.
- Data quality varies across and within geographies due to differences in:
 - Income and internet access
 - Labor market formality
 - LinkedIn language coverage
 - Use and reliance on technology and LinkedIn, specifically
- Given variance in data quality, more granular data cuts will not be available in all countries.



LinkedIn data—like most privately-sourced data—has limitations, so it should always be used to supplement, not replace, publicly-sourced data

Privacy

- We do not share “micro-data” or member level data
- Even aggregated data must maintain and prioritize member privacy, for example:
 - Geography is based on member reported data, not physical location / IP address
 - Minimum thresholds prevent the sharing of data for granular labor market segments

Focus on Labor Supply

- Our data is largely supply-based as it pulls from our 1B+ members; data on job postings (labor demand) is not as easily standardized.
- Data reflects supply as reported by members. To the extent that our taxonomies differ from standards (e.g. ISIC and ISCO), this reflects differences reflected by our members.

Data for Impact (DFI) supports three collaborative models with partners



INNOVATE

Partners leverage “off-menu” data for novel, high-impact labor market insights that inform policy

- DFI and Germany’s leading labor market think tank, IAB, joined forces to develop a new indicator
- The [Reallocation Radar](#) predicts cross-industry career changes, informing labor market conversations in the German market



INFORM

Partners request “on-menu” data to inform specific, well-scoped investments, programs, or reports

- World Bank partners requested LinkedIn data for multi-billion dollar [country development strategies](#)
- These strategies leveraged data on gender inequities and industry hiring to inform relevant labor market interventions



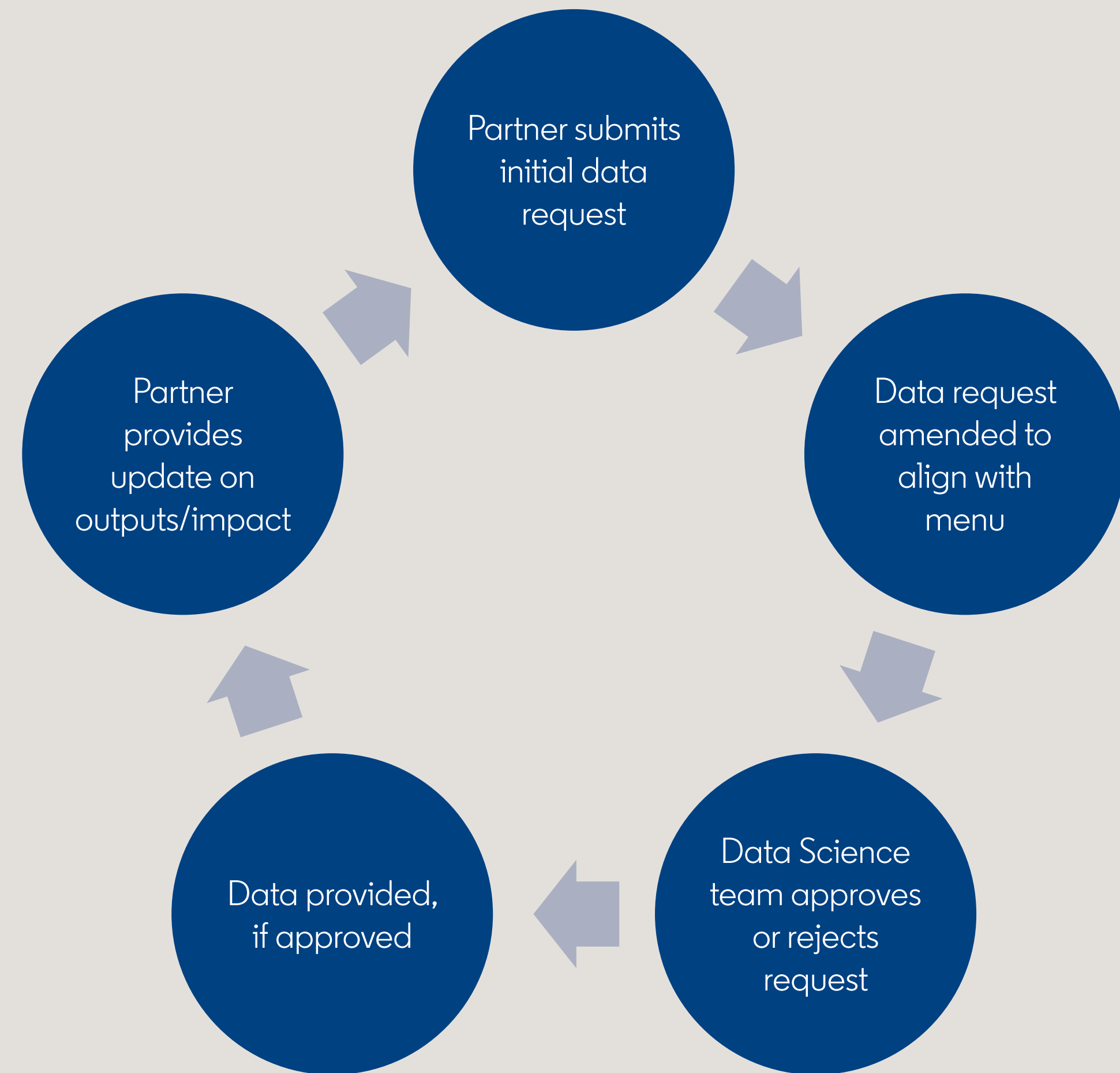
INTEGRATE

Statistical, fiscal, and labor partners integrate “on-menu” data for economic monitoring

- The German Statistical Authority, Destatis, now receives monthly LinkedIn data on industry hiring
- Destatis [validated use of LinkedIn data](#), identifying it as a key source for faster, actionable labor market insights

LinkedIn's Economic Graph and Research Insights team assesses data requests based on feasibility, alignment with key priorities, and potential impact

- We cannot fulfill all data requests
- The Data Science team assesses requests based on the following criteria:
 - Feasibility: Is the data request aligned with the DFI menu? Can LinkedIn data help answer the Partner question for the relevant geography and population?
 - Priority Alignment: Does the project address the AI/digital transition, skill-based career pathways, gender equity, or the green economy?
 - Potential Impact: Is the partner effort a funded operation? A public service? Targeted research? A “fishing expedition”?



Indicator Samples

LinkedIn Hiring Rate (Monthly)

Indicator Description

The LinkedIn Hiring Rate (LHR) measures hiring activity based on members changing jobs on their LinkedIn profiles. LHR is able to reflect changes in hiring activity during different macroeconomic events, as well as sector and talent-level nuances in hiring activity. See methodology [here](#).

Use Cases

- Economic monitoring by the German Statistical Authority, Destatis – [here](#)
- Programmatic planning by the Inter-American Development Bank – [here](#)
- Fiscal analysis of Asia and the Pacific by the International Monetary Fund – [here](#)

Available Dimensions



National



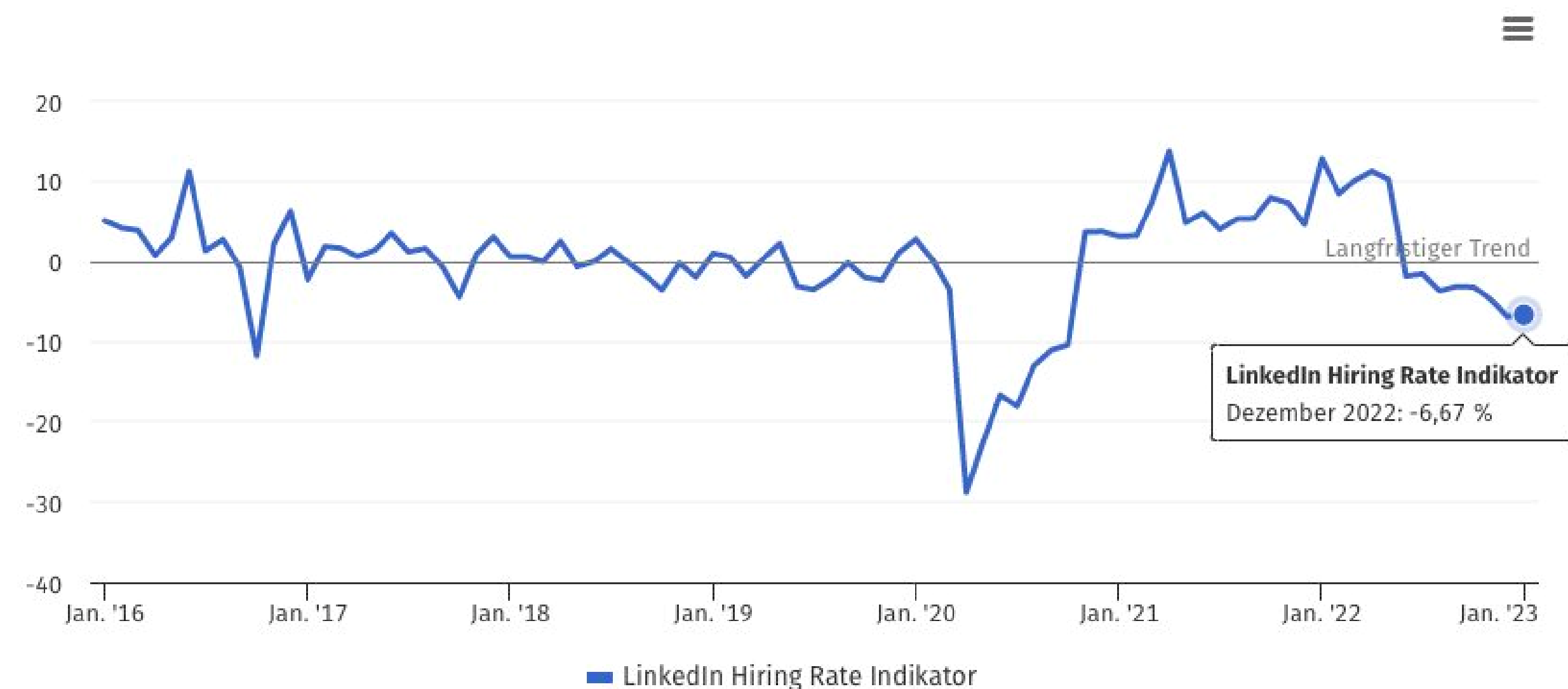
Industry



Skill Groups

Development of the German labor market based on the LinkedIn hiring rate ⓘ

Deviation from the long-term trend of new hires in percent, calendar and seasonally adjusted



Female Representation (Annual)

Indicator Description

- Share of members inferred as female, overall and by seniority
- Share of hires inferred as female, overall and by seniority

Use Cases

- 2024 Global Gender Gap Report by the World Economic Forum – [here](#)
- Analysis of gender diversity in the green economy by the Inter-American Development Bank – [here](#)
- European Bank for Reconstruction and Development inclusive green strategy – [here](#)

Available Dimensions



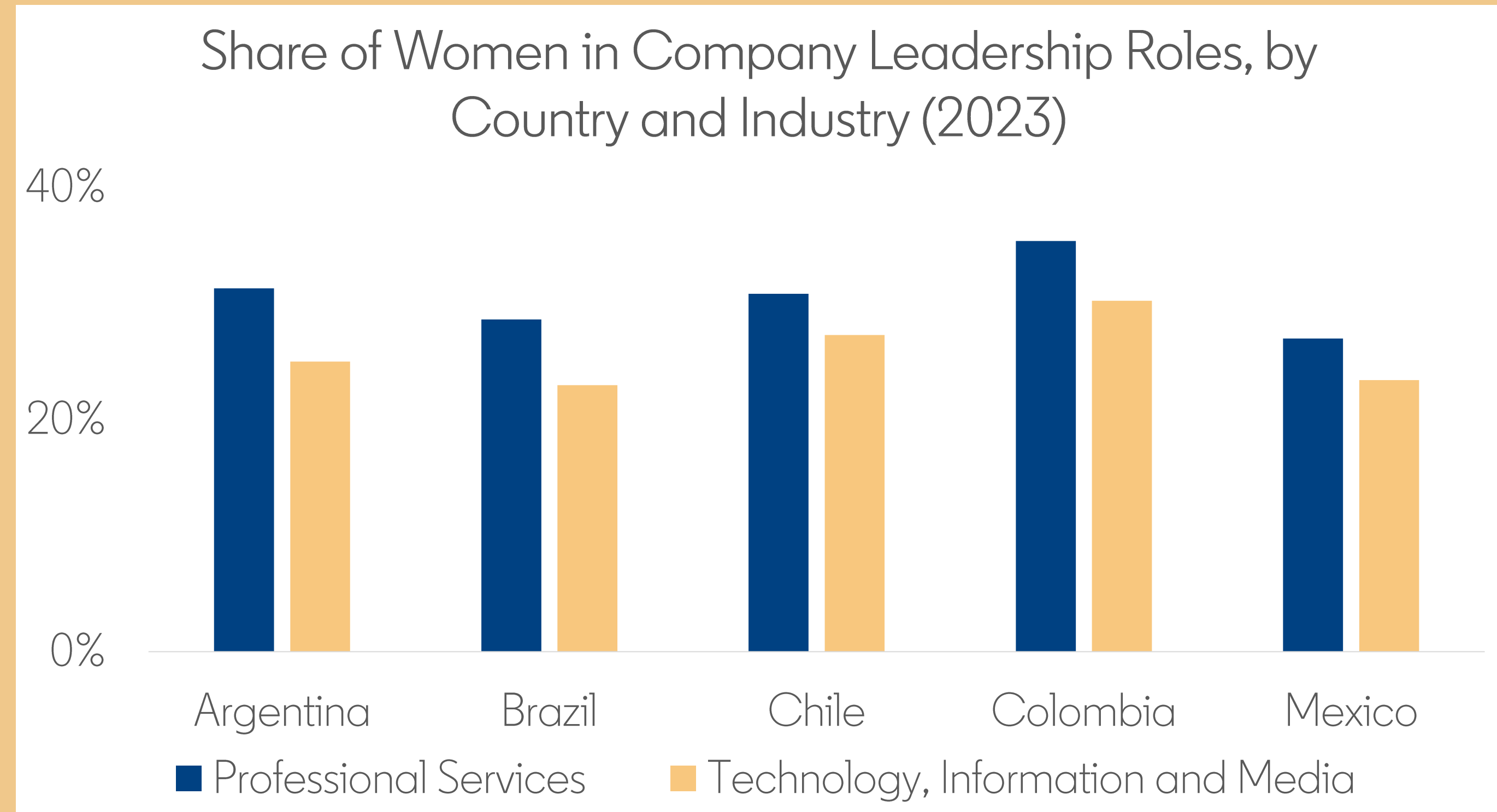
National



Industry



Skill Groups



Career Transitions

(Annual)

Indicator Description

LinkedIn members leaving jobs in Industry A entering jobs in Industry B, as a share of all LinkedIn members leaving jobs in Industry A and going to industries for which there were a sufficient number of transitions. Also provided is the share of LinkedIn members leaving jobs in Industry B entering jobs in Industry A.

Use Cases

- World Bank Jobs Flagship research used time series data on industry transitions to assess national economic transitions

Available Dimensions

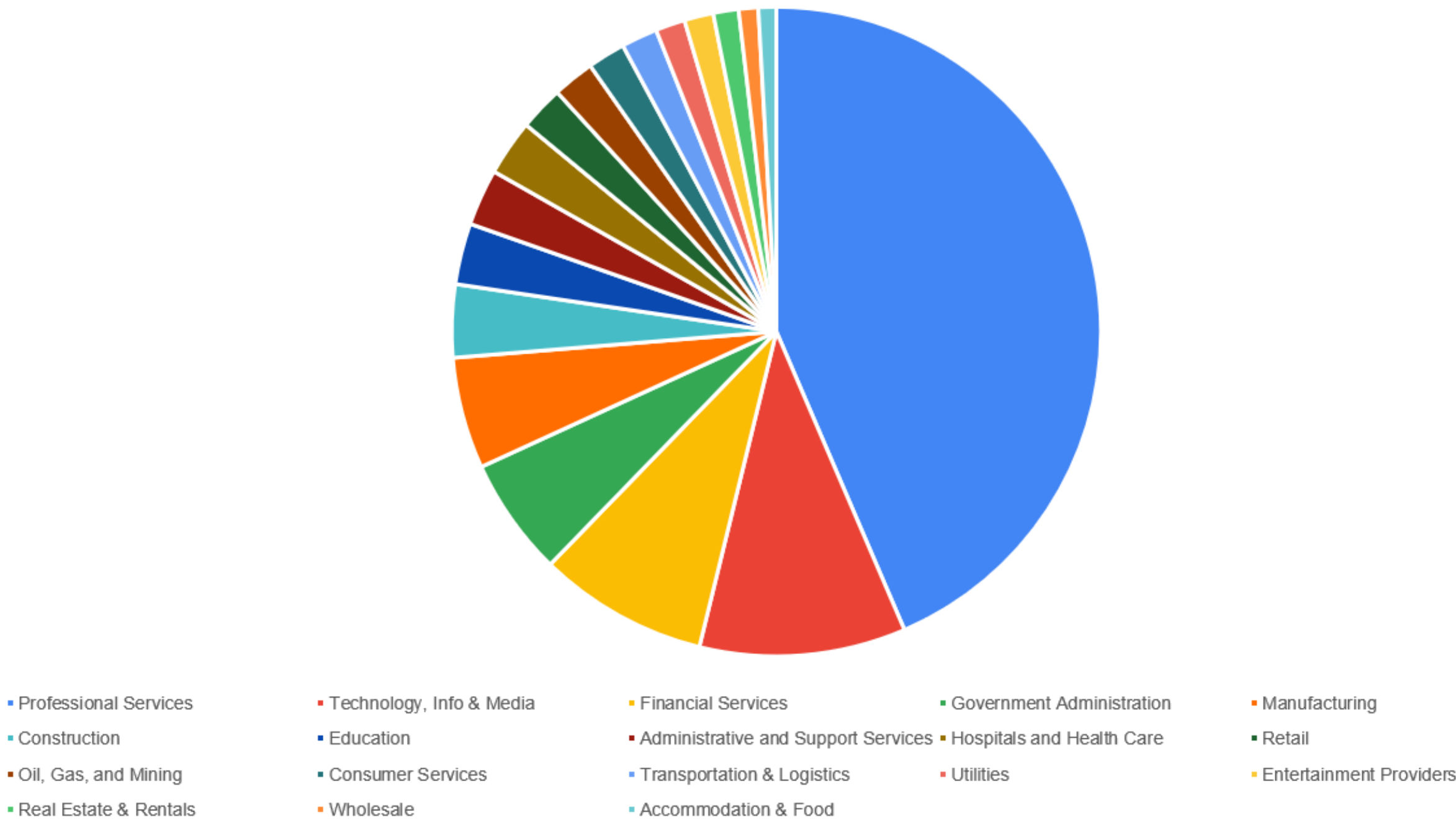


National



Industry

Share of Job Transitions Out of Professional Services by Destination Industry
(Argentina, 2022)



Reallocation Radar (Semi-annual)

Indicator Description

The Reallocation Radar, developed with leading German labor market think tank IAB, maps cross-industry job transitions by averaging:

- Current switches: the current ratio of people changing to a new job in a different industry
- Future switches: the current ratio of applications for jobs in a different industry relative to total applications

Use Cases

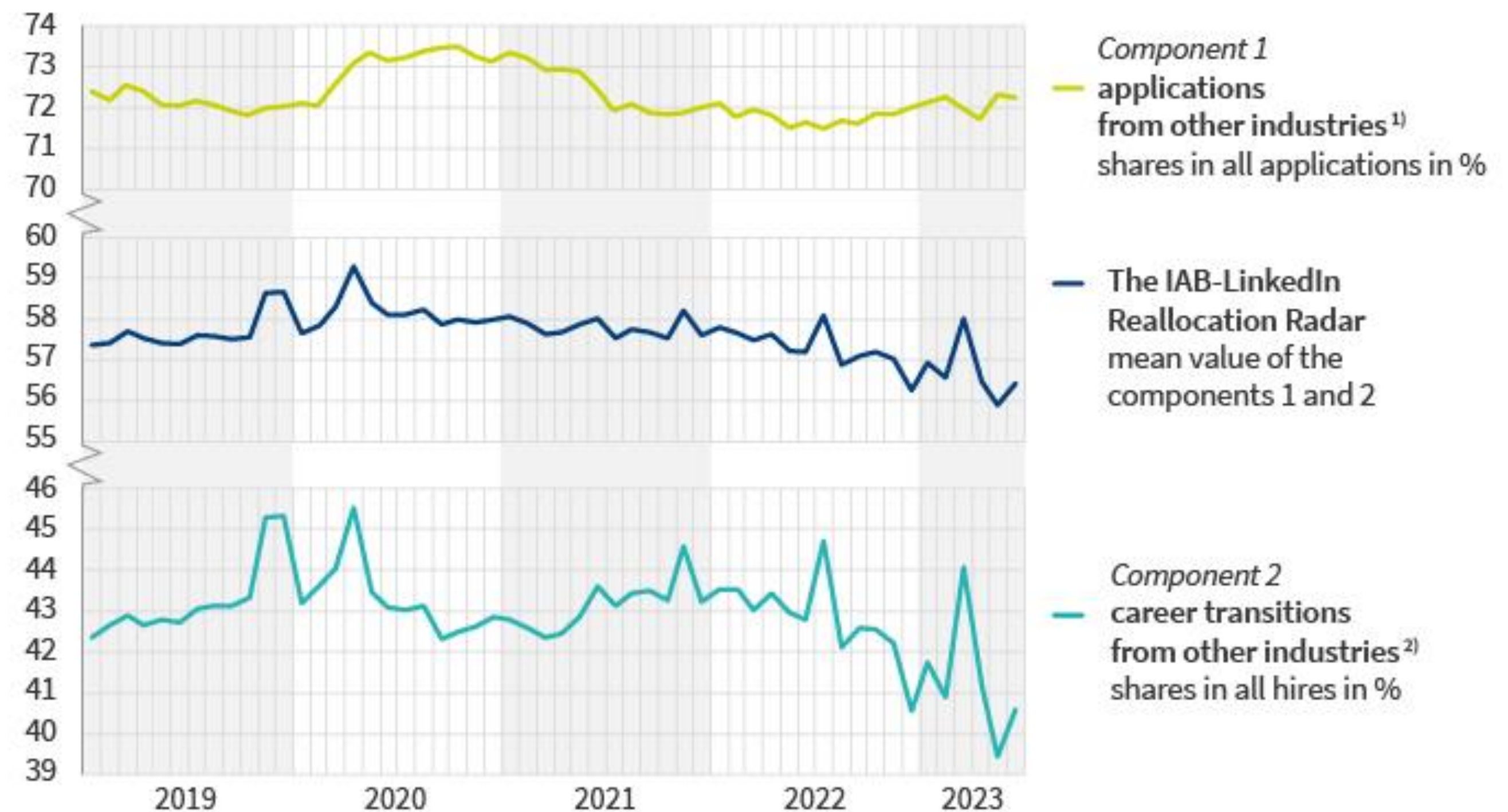
- German Reallocation Radar – [here](#)

Available Dimensions



National

Figure: The IAB-LinkedIn Reallocation Radar



Concentration

(Monthly or Annual - varies)

Indicator Description

The share of LinkedIn members in a country and/or industry with specific categories of skills, including AI Engineering, AI Literacy, Cybersecurity, and Electrical Vehicle.

Use Cases

- Analysis AI skill growth across the labor force in OECD's 2024 Digital Economic Outlook – [here](#)
- Development of youth trainings for electric vehicle production in Mexico – [here](#)
- US National Science Foundation efforts to expand the cybersecurity workforce – [here](#)

Available Dimensions



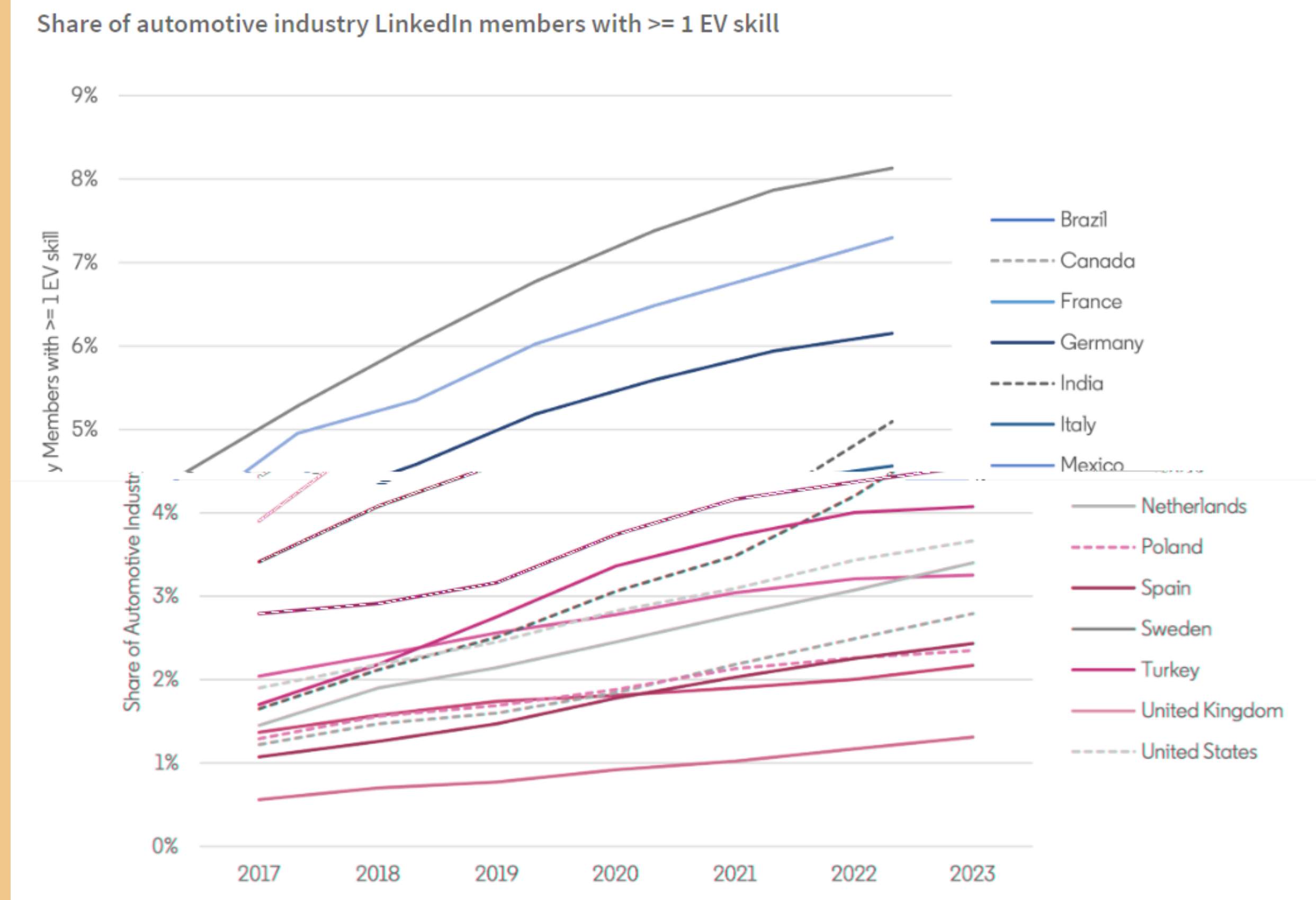
National



Industry



Gender



Skill Genome

(Annual)

Indicator Description

An ordered list of the 'most characteristic skills' of a country, industry, or occupation. Pooled data draws from skills added across years, while flow data draws from skills added during the specified year. See the World Bank-validated methodology in the appendix and [here](#).

Use Cases

- World Bank investment planning for Argentina focused on women’s career advancement – [here](#)
- UN and World Bank design of digital training programs in MENA – [here](#)
- ILO and Microsoft’s design of training programs for Women in Digital Business – [here](#)

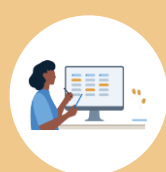
Available Dimensions



National



Industry



Occupation
(pooled only)

Women in the ICT sector have more non-technology skills than men

Top 10 most characteristic skills in Argentina’s ICT sector, 2021

Women	Men
Spanish	Scrum*
Scrum*	SQL*
Agile Methodologies*	Git*
Jira*	JavaScript*
SQL*	MySQL*
Can-do approach	Microsoft SQL Server*
Interpersonal relationships	Node.js*
Portuguese	Agile Methodologies*
Liability	React.js*
Microsoft SQL Server*	Spanish

Source: LinkedIn. Note: The "*" indicates a technology skill.

FIGURE V-6:

Most-Representative Skill Groups for the Online Media Industry Globally

- | | |
|----------------------|-----------------------|
| 1. Social Media | 6. Advertising |
| 2. Journalism | 7. Graphic Design |
| 3. Editing | 8. Photography |
| 4. Writing | 9. Oral Communication |
| 5. Digital Marketing | 10. Digital Literacy |

Source: Authors’ calculation using LinkedIn data.

Skill Penetration (Annual)

Indicator Description

The share of the most representative skills that come from a specific skills group. Pooled data draws from skills added across years, while flow data draws from skills added during the specified year. See the World Bank-validated methodology in the appendix and [here](#).

Use Cases

- Inter-American Development Bank assessed firm use of digital technologies by country – [here](#)
- World Bank strategic investment planning in Panama and Costa Rica – [here](#)

Available Dimensions



National



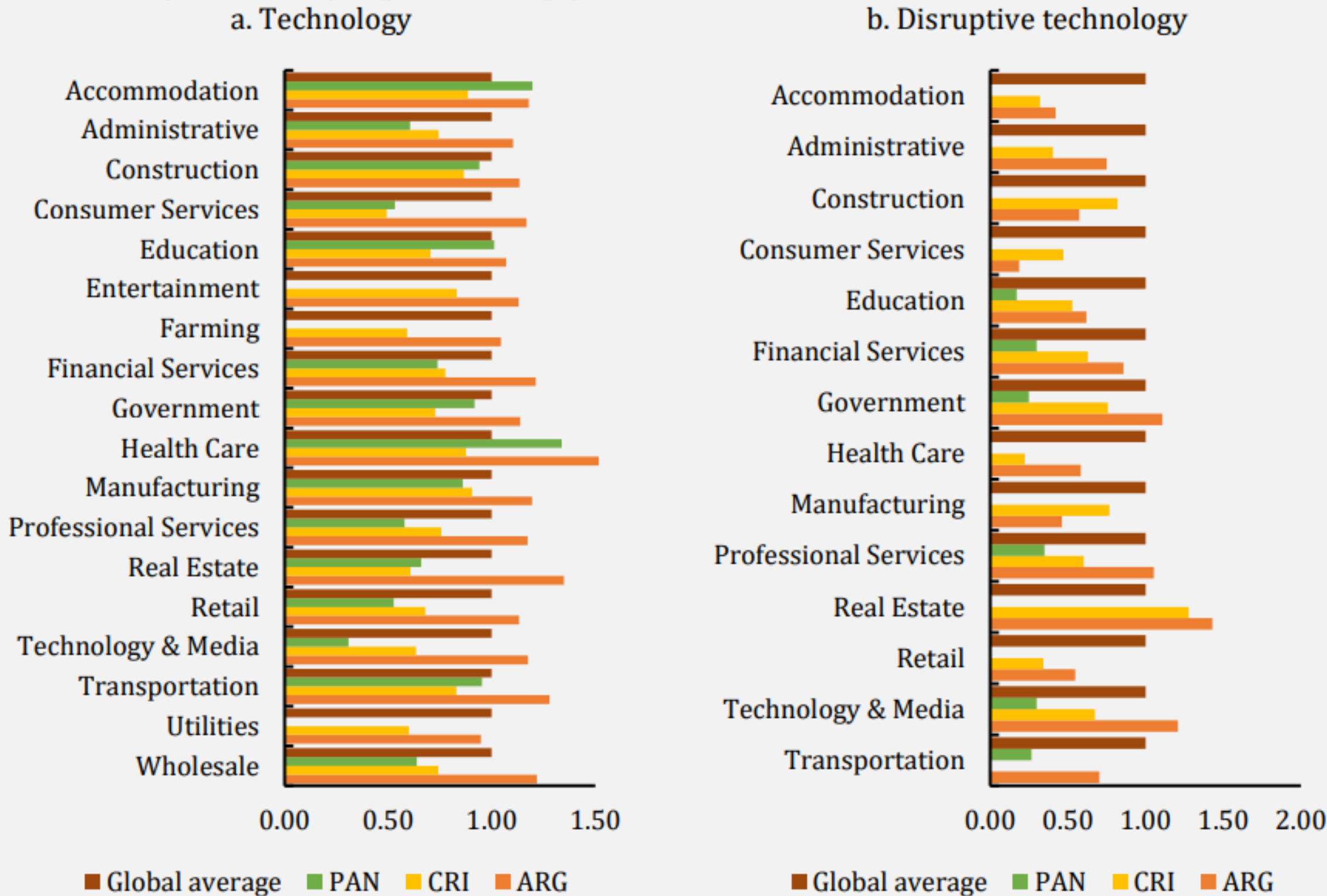
Industry



Skill Groups

Figure B4.1.1: Penetration of Technology and Disruptive Technology Skills, 2022

Relative skills penetration (1 = global average)



Source: [LinkedIn](#) 2022.

Note: ARG = Argentina; CRI = Costa Rica; PAN = Panama.

Appendix: Methodological Notes

Specialized Skill Categories

Skills are annotated as pertaining to specific skill categories, which can be applied as indicator dimensions

Skill Group Category	Description
Soft Skills	Non-cognitive skills or personality traits valued in the labor market but not assessed by achievement tests. IQ or achievement tests cannot predict these skills.
Business Skills	Knowledge and skills required to start or operate an enterprise. Examples include Business Management, Project Management, Entrepreneurship.
Tech Skills	Defined as a range of abilities to use digital devices, communication applications, and networks to access and manage information. They enable people to create and share digital content, communicate and collaborate, and solve problems.
Disruptive Tech Skills	Skills associated with developing new technologies that are expected to impact labor markets in the coming years. Examples include Robotics, Genetic Engineering, and Artificial Intelligence. Artificial Intelligence can be isolated as a skill group category itself (see OECD.AI).
AI Skills (Engineering and Literacy)	AI skills are technical skills that are used in building AI technologies. Can also be referred to as "AI Technical Skills" and "AI Engineering Skills". AI Literacy skills are applied in using AI technologies. Can also be referred to as "AI Aptitude Skills".
Green Skills	Green skills are those that enable the environmental sustainability of economic activities. See more on our green skills methodology here .

Specialized Skill Categories

Examples

- Each of these categories have 1k+ skills and change over time as LinkedIn's skills taxonomy is updated.
- While we will not share the full skills list, we provide this illustrative list of examples from each category.
- All skill lists are provided in [this report](#) but lists may change over time.

Soft	Business	Disruptive Tech	Digital	Green
Project-based Learning	TVC	Turbojet	Very-Large-Scale Integration (VLSI)	Sustainable fashion
Quick Study	Text Marketing	Turbomachinery	Virtuoso	Environmental Services
SCORM	Traditional Media	Unmanned Vehicles	VxWorks	Oil Spill Response
Self Learning	Transit Advertising	Wind Tunnel	X86	Climate
Service Orientation	Unica	Wind Tunnel Testing	Xilinx	Sustainable Growth
Social Learning	Video Advertising	A/B Testing	Xilinx ISE	Surface Water
Study Skills	Web Analytics	ANOVA	ZigBee	Occupational Safety and Health Advisor
eCollege	Web Strategy	Adobe Analytics	3GPP2	Sustainable Business Strategies
Advising People	WebTrends Analytics	Alteryx	802.11b	Solar Systems
Body Language	Webmaster Services	Analytics	802.1x	Sustainable Landscapes
Business Letters	comScore	Anomaly Detection	ATM Networks	ISO 14001
Client-focused	Acquisition Marketing	Apache Flink	Adobe Marketing Cloud	Solar Energy
Communication	Affiliate Management	Apache Mahout	Alcatel	Recycling
Conference Speaking	Affiliate Marketing	Apache Spark	Alteon	Renewable Energy
Diction	Affiliate Networks	Bayesian inference	Amazon CloudFront	Environmental Awareness

Skills Genome

Methodological Notes

Goal

Identify the most relevant skills for groups of members holding specific occupations in specific countries and specific geographies.

Challenge

A set of generic skills (such as Microsoft Office) often occupies the top spots in the skills vector for many occupations.

Solution

TF-IDF downweights skills that are common across other occupations. The method is a combination of skill popularity and uniqueness.

Data Analyst Skills in Spain:
Popular Vs. Popular AND Unique (Skills Genome)

Popular	Popular AND Unique
Data Analysis	SQL
SQL	Tableau
Python	Python
Tableau	Data Analysis
Microsoft Excel	Hive
Microsoft Office	R
R	Machine Learning
Microsoft PowerPoint	Data Mining
Microsoft Word	Post-GRE SQL
Hive	Data Visualization

Interpretation

The most distinct skills claimed by LinkedIn members working as Data Analysts in Spain include SQL, Machine Learning, and Data Visualization.

Skills Penetration

Methodological Notes

Goal

Determine how many of the most distinct 50 skills, for each occupation in each country, belong to a given skill group (e.g. Tech Skills, Soft Skills, etc.).

Challenge

LinkedIn’s occupational distribution and coverage varies by country, even within the same industry.

Solution

Compare each country’s skill penetration to a global composite benchmark based on that country’s occupational distribution.

Tech Skills in Healthcare Industry

Ctry	Industry	AVG SP	GLOBAL SP	RELATIVE SP
X	Healthcare	0.1	0.2875	0.3478
Y	Healthcare	0.3	0.3625	0.8276
Z	Healthcare	0.5	0.333	1.5015

Interpretation

On average, tech skills comprise 10% of the occupational skill genomes in Country X’s Healthcare Industry. Holding constant for differences in occupational distributions, this penetration of tech skills is ~35% of the global average for this industry.

Skill Penetration (SP) Calculations

Methodological Notes

1. Start with Skills Penetration data at Country/Industry/Occupation level

Tech Skills Penetration by Ctry/Ind/Occ*

Country	Industry	Occupation	Skill Penetration (SP)
X	Healthcare	Nurse	0.05
X	Healthcare	Accountant	0.15
Y	Healthcare	Nurse	0.25
Y	Healthcare	Surgeon	0.35
Z	Healthcare	Nurse	0.60
Z	Healthcare	Surgeon	0.50
Z	Healthcare	Accountant	0.40

2A. AVERAGE skill penetration based on occupations at country-industry level

AVG Tech Skills Penetration by Ctry/Ind

Country	Industry	Calculation	AVG SP
X	Healthcare	$(0.05+0.15)/2$	0.1
Y	Healthcare	$(0.25+0.35)/2$	0.3
Z	Healthcare	$(0.60+0.50+0.40)/3$	0.5

2B. Calculate GLOBAL industry skill penetration from occupational mix

Tech Skills Penetration by Ind/Occ (Global)

Country	Occupation	Calculation	Skill Penetration
-	Nurse	$(0.05+0.25+0.60)/3$	0.3
-	Accountant	$(0.15+0.40)/2$	0.275
-	Surgeon	$(0.35+0.50)/2$	0.425

GLOBAL Tech Skills Penetration by Ctry/Ind

Country	Industry	Calculation	GLOBAL SP
X	Healthcare	$(0.3+0.275)/2$	0.2875
Y	Healthcare	$(0.3+0.425)/2$	0.3625
Z	Healthcare	$(0.3+0.275+0.425)/3$	0.333

3A. Calculate RELATIVE industry skill penetration based on global SP

RELATIVE Tech Skills Penetration by Ctry/Ind

Country	Industry	Calculation	RELATIVE SP
X	Healthcare	$0.1 / 0.2875$	0.3478
Y	Healthcare	$0.3 / 0.3625$	0.8276
Z	Healthcare	$0.5 / 0.333$	1.5015

3B. Final Outputs are AVG, GLOBAL, and RELATIVE Skills Penetration by Ctry/Ind

All Tech Skills Penetration by Ctry/Ind

Ctry	Ind	AVG SP	GLOBAL SP	RELATIVE SP
X	Healthcare	0.1	0.2875	0.3478
Y	Healthcare	0.3	0.3625	0.8276
Z	Healthcare	0.5	0.333	1.5015

*Ctry is Country. Ind is Industry. Occ is Occupation.

Thank you