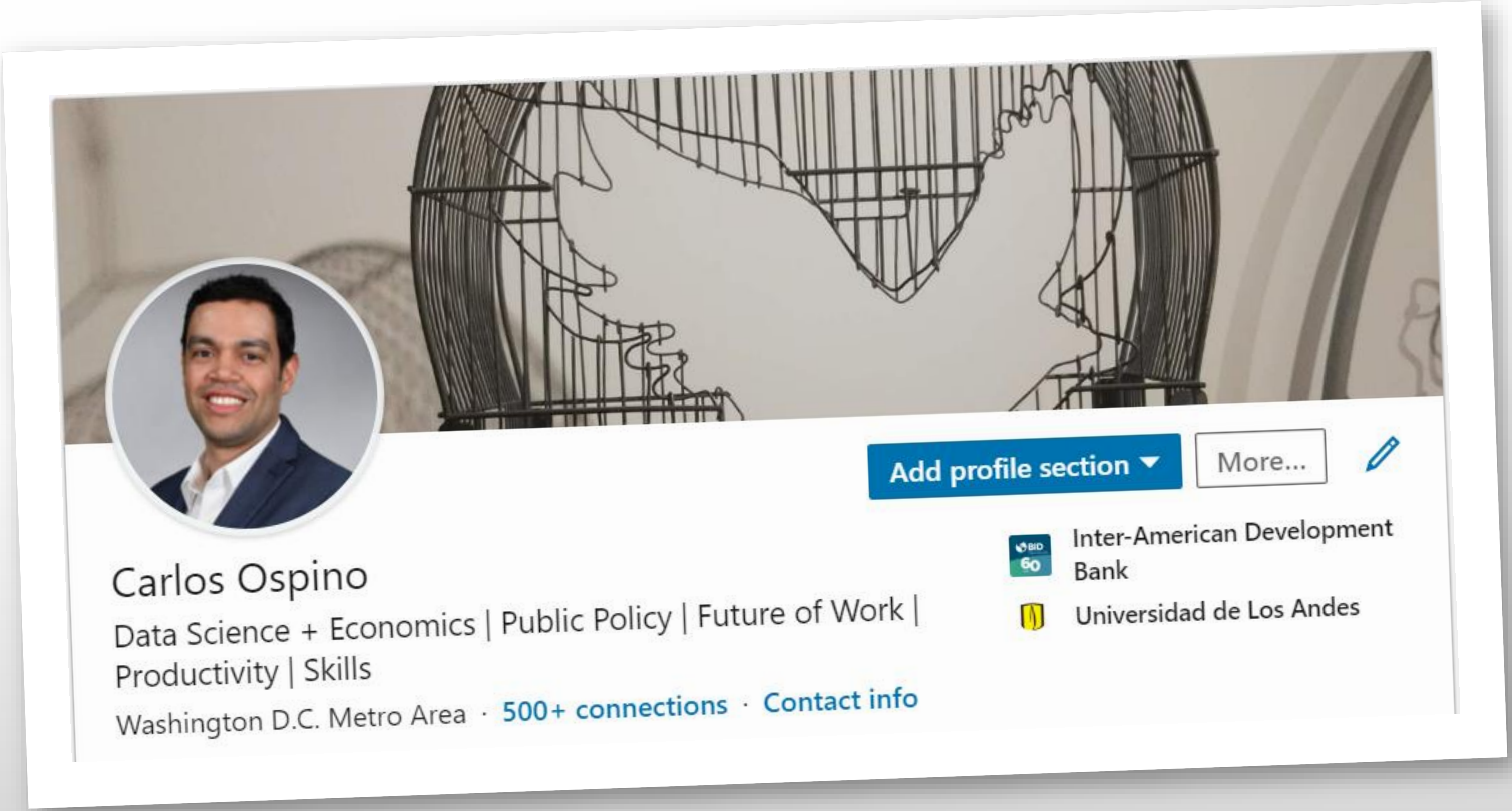
HOW FAR CAN YOUR SKILLS TAKE YOU?

Understanding skill demand changes due to occupational shifts and the transferability of workers across occupations

LinkedIn

BID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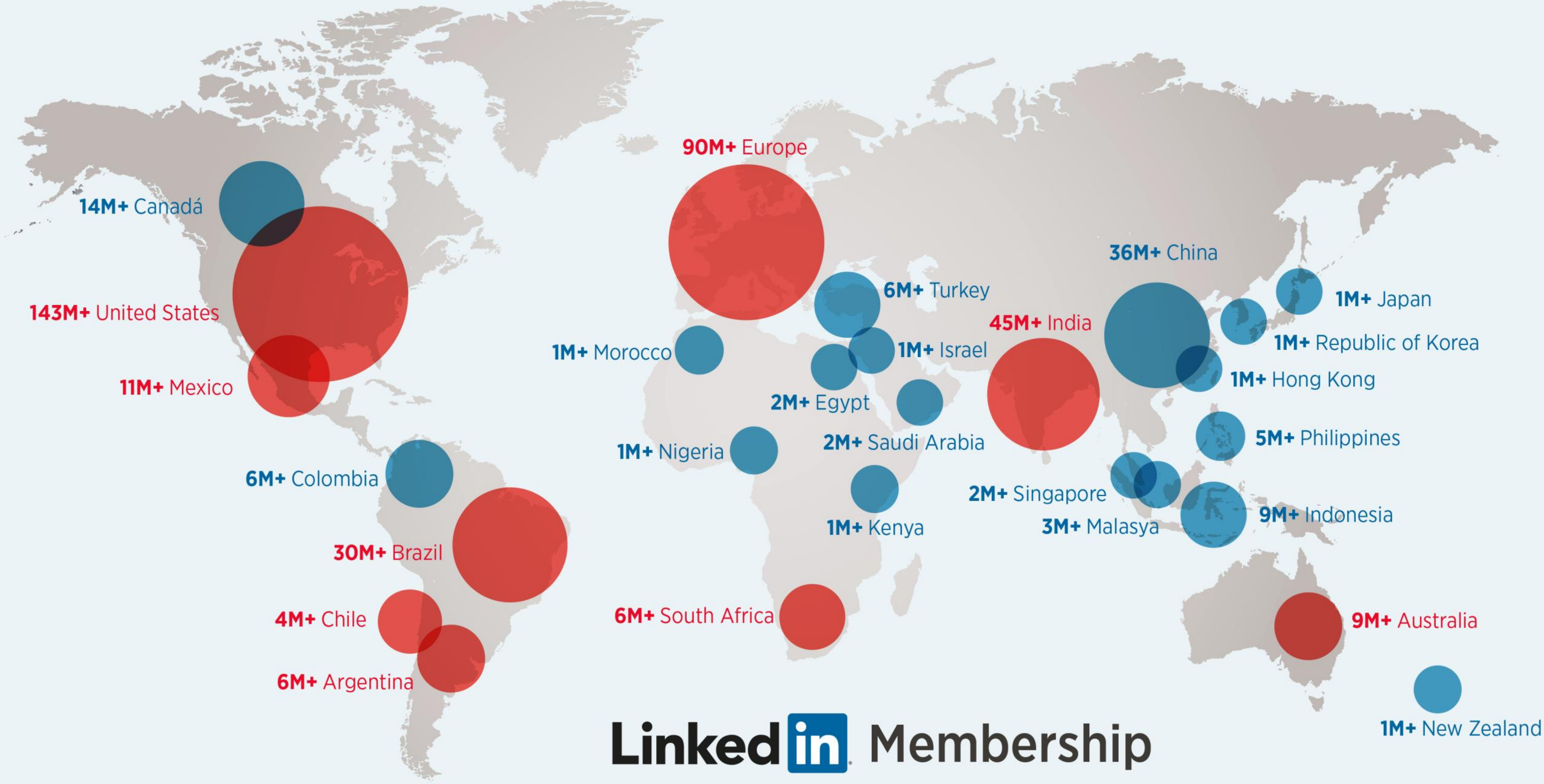

90M+ Europe
14M+ Canadá
143M+ United States
11M+ Mexico
6M+ Colombia
30M+ Brazil
4M+ Chile
6M+ Argentina
1M+ Morocco
1M+ Nigeria
6M+ South Africa
6M+ Turkey
1M+ Israel
2M+ Egypt
2M+ Saudi Arabia
1M+ Kenya
45M+ India
36M+ China
1M+ Japan
1M+ Republic of Korea
1M+ Hong Kong
5M+ Philippines
2M+ Singapore
3M+ Malasya
9M+ Indonesia
9M+ Australia
1M+ New Zealand
LinkedIn Membership

WHAT’S UNIQUE ABOUT LINKEDIN’S DATA?

Hires

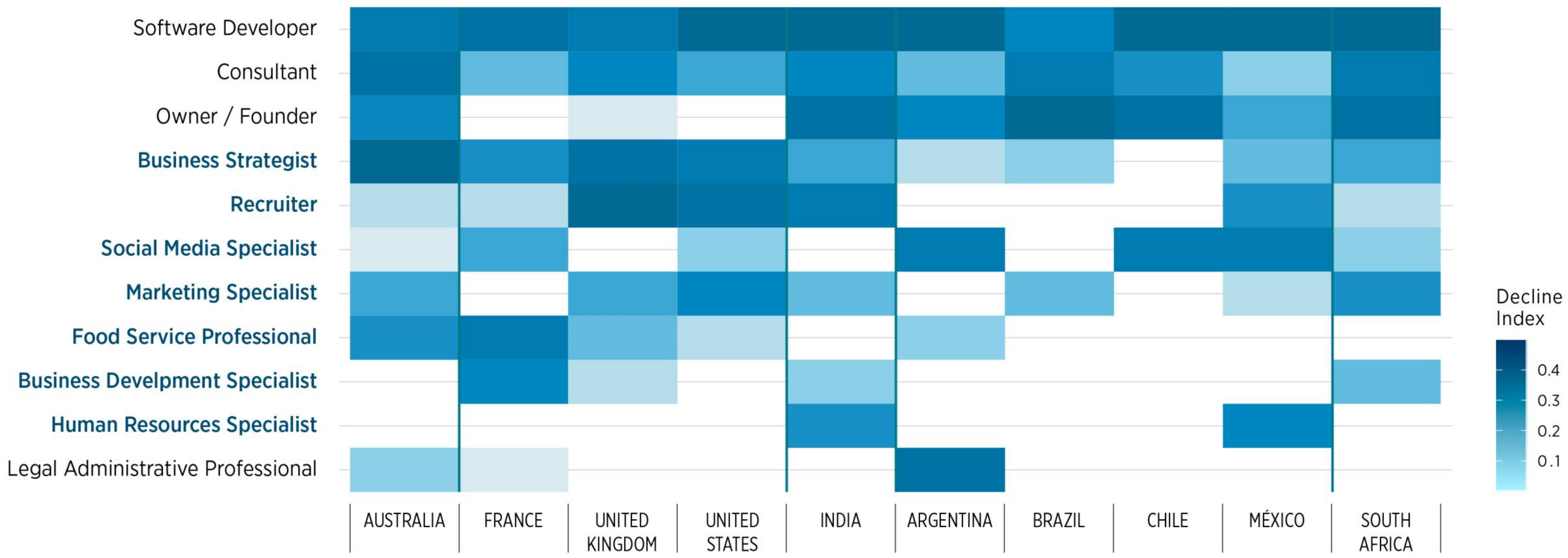
Occupations

Skills

SOFTWARE DEVELOPER IS THE FASTEST GROWING OCCUPATION

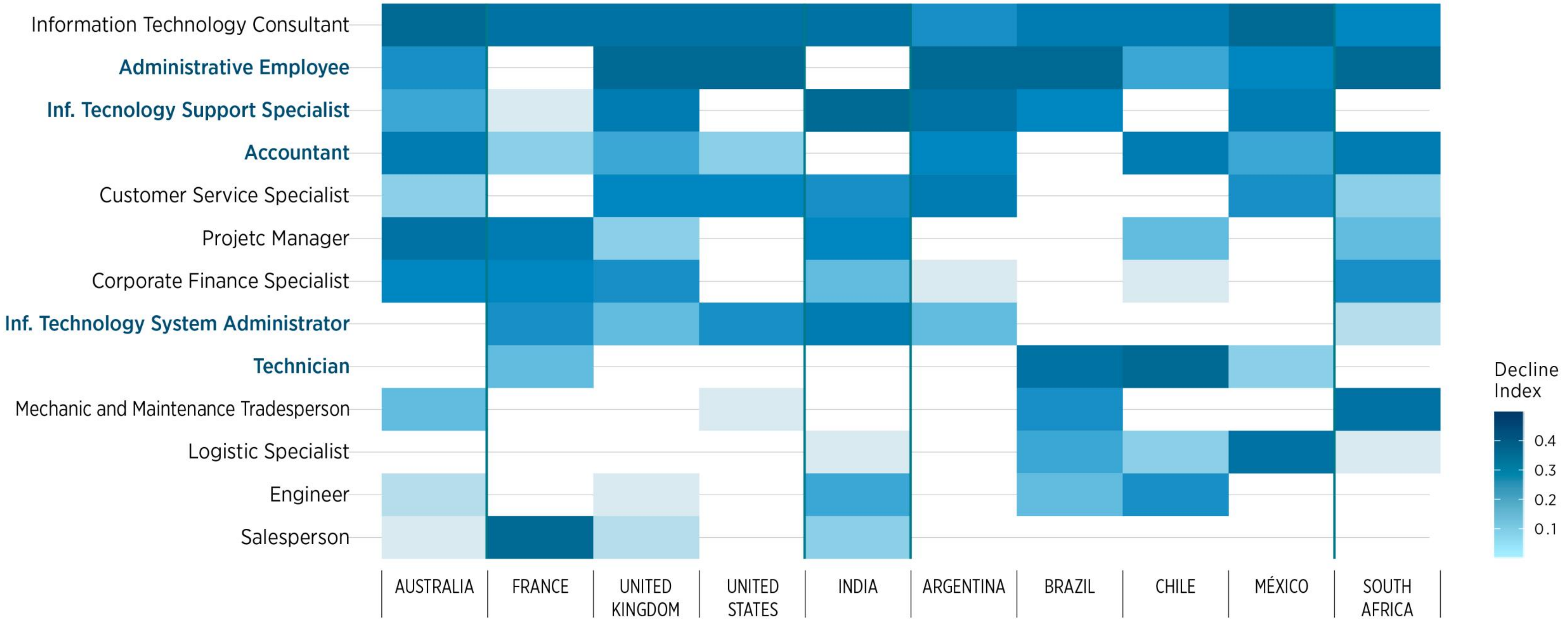
BUT NOT ALL TECH-FOCUSED ROLES ARE ON THE RISE

PEOPLE-CENTRIC ROLES ARE ON THE RISE



Most emerging occupations across countries

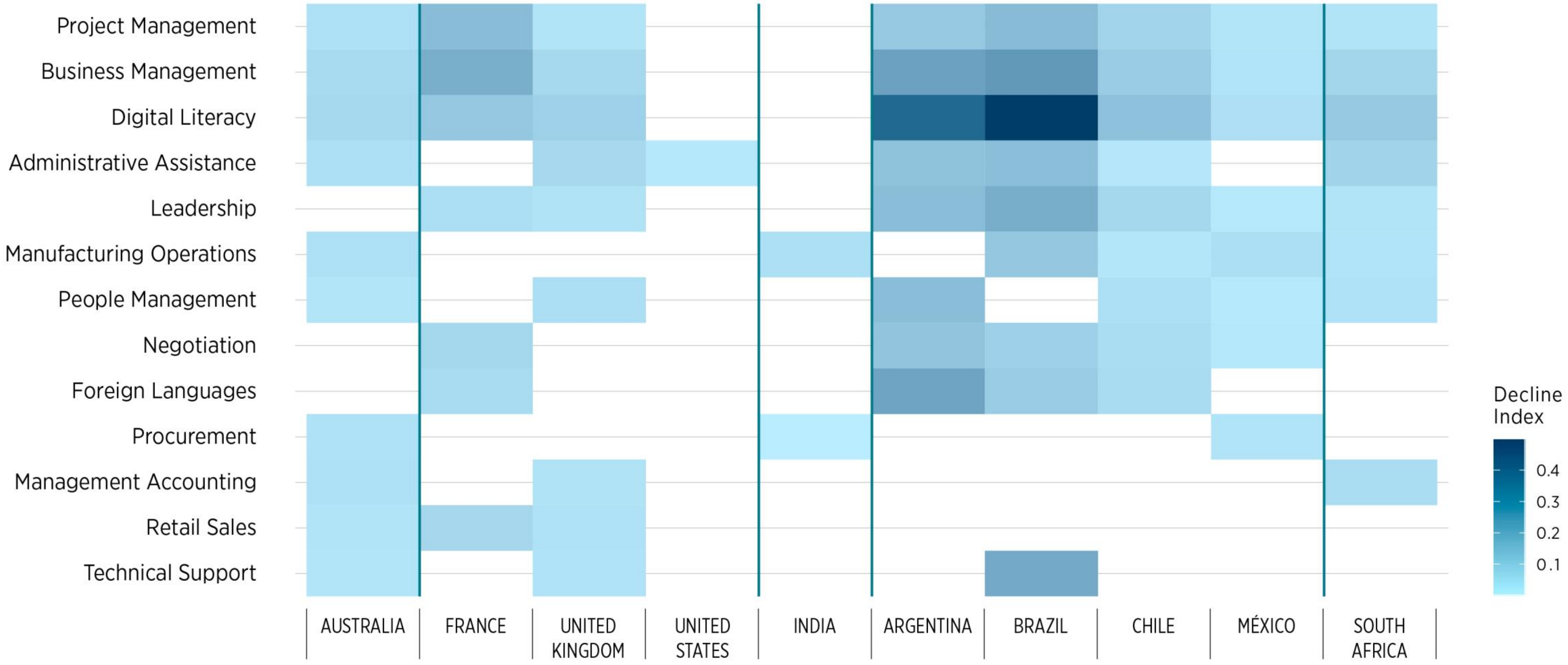
ADMINISTRATIVE ROLES AND TECH SUPPORT ARE DECLINING



Most emerging occupations across countries

DIGITAL TOOLS AND ADVANCED DIGITAL SKILLS ARE IN HIGH DEMAND

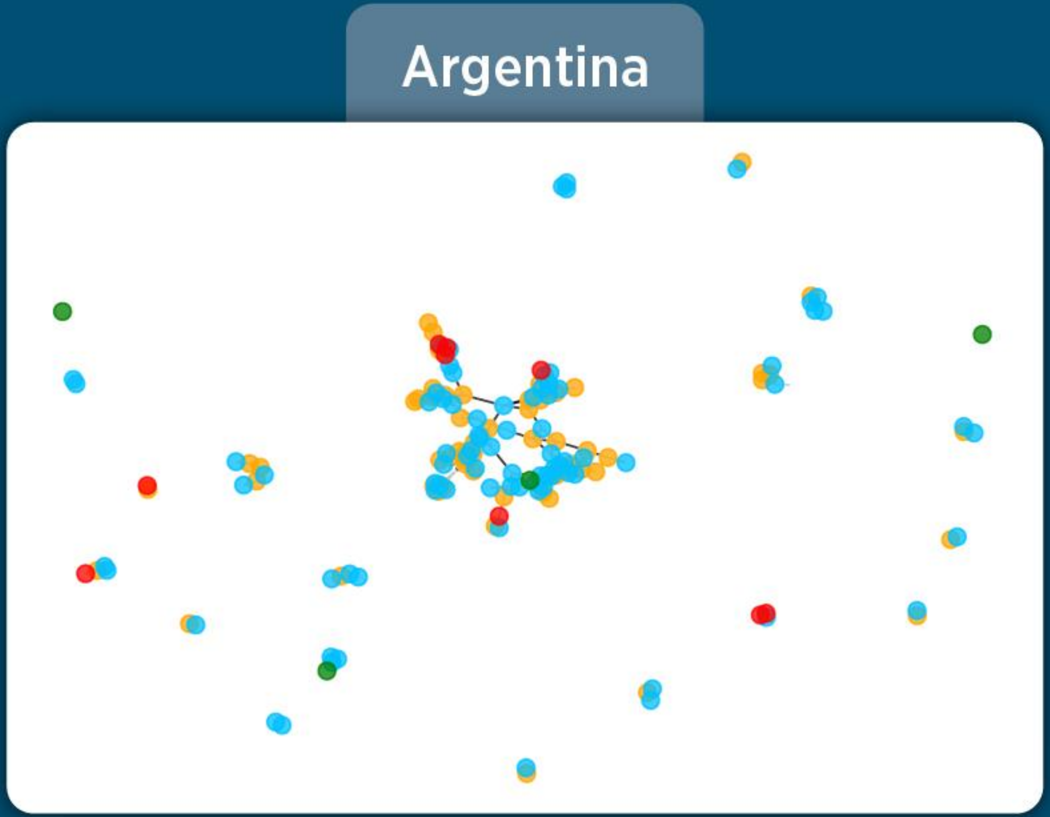
BUT **BASIC DIGITAL SKILLS** AND **MANAGEMENT SKILLS** ARE ON THE DECLINE

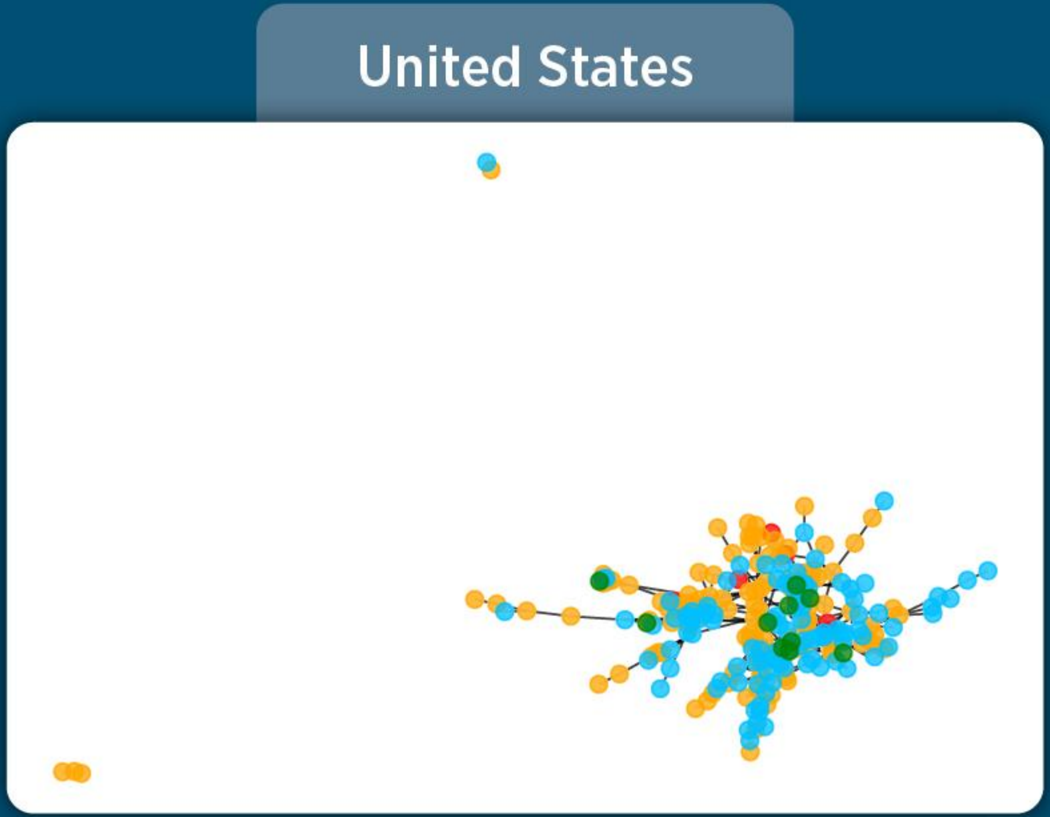


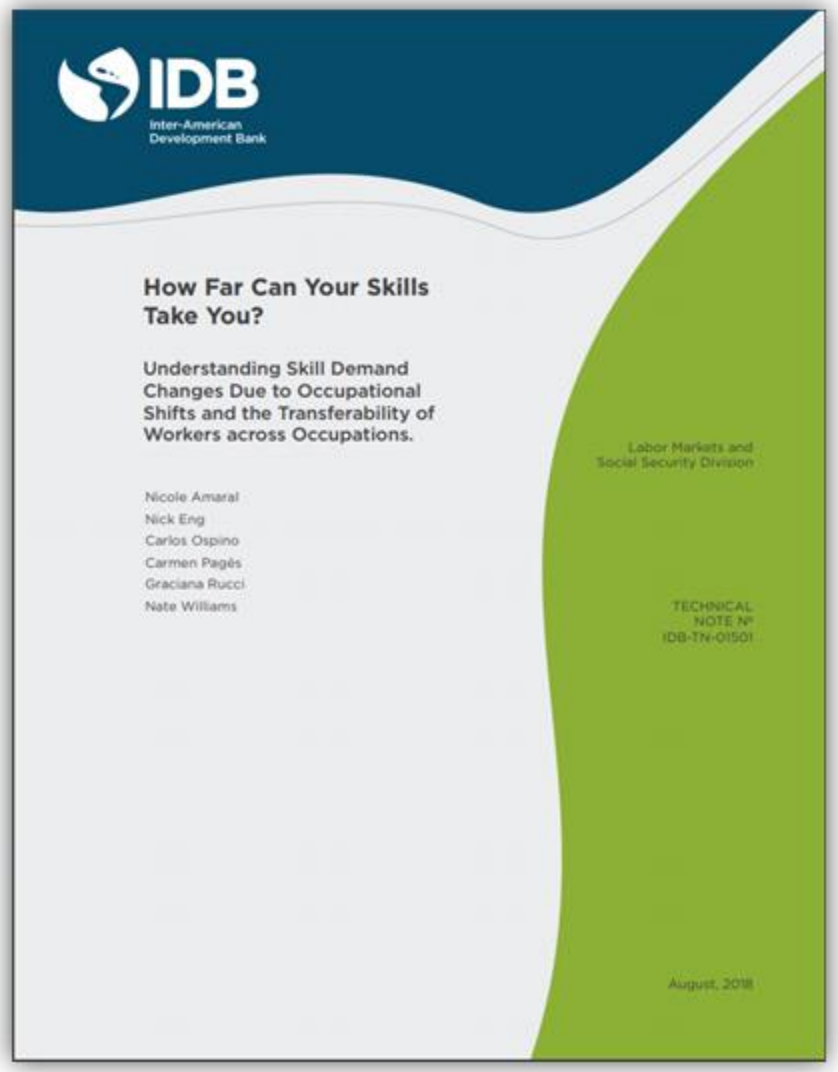
Most emerging occupations across countries

WE CAN CREATE A GPS FOR THE LABOR MARKET

A NETWORK OF OCCUPATIONS CONNECTED BY THE SKILLS THEY SHARE



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How Far Can Your Skills Take You?

Understanding Skill Demand Changes Due to Occupational Shifts and the Transferability of Workers across Occupations.

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BRINGING INNOVATIVE INSIGHTS AND SOLUTIONS TO LATIN AMERICA AND THE CARIBBEAN

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3

The future of work in Latin America and the Caribbean

What are the most in-demand occupations and emerging skills in the region?

IDB
Inter-American Development Bank

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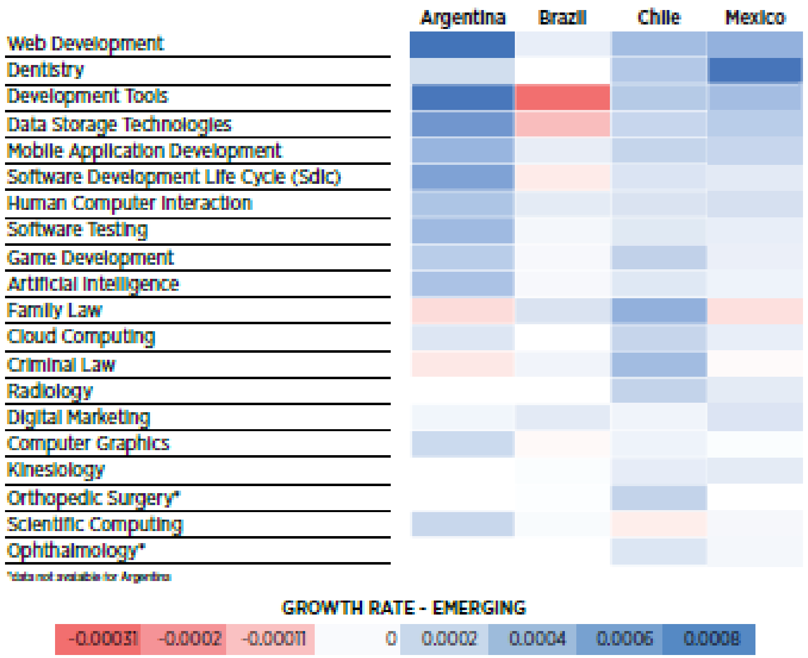
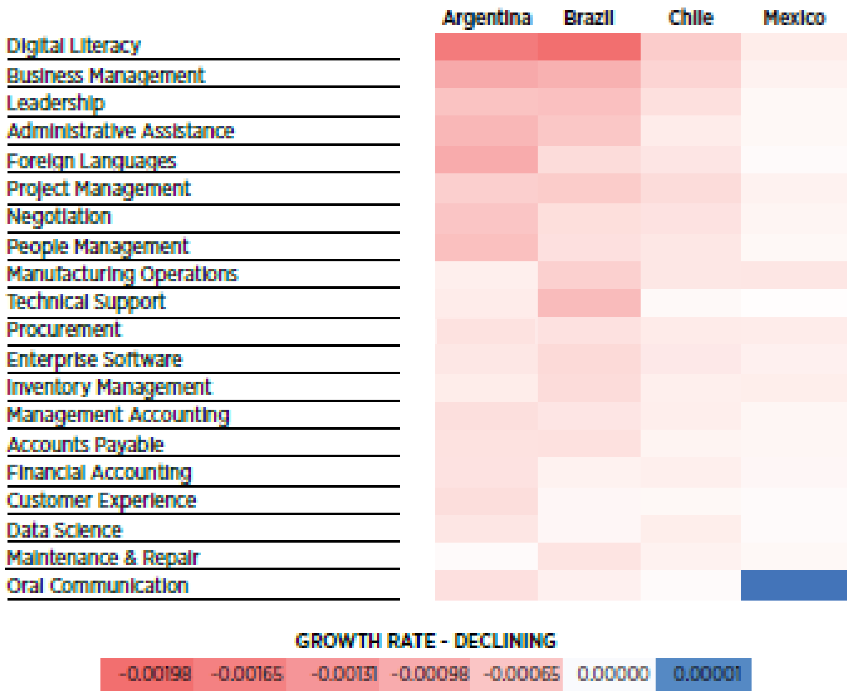
FIGURE 8. EMERGING AND DECLINING SKILLS (2015-2017)

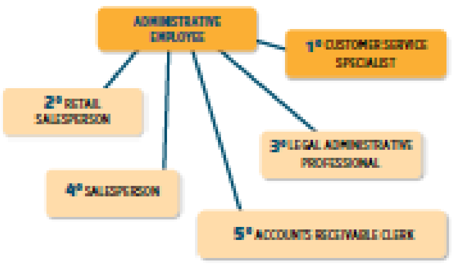




Source: *How far can your skills take you?* (Amaral et al., 2018). The figure shows the most in-demand and declining skills, sorted by their average increase in the four Latin American countries analyzed (Argentina, Brazil, Chile and Mexico). It corresponds to changes in the demand for skills as a result of change in occupations.

ARGENTINA
ADMINISTRATIVE EMPLOYEE

CLOSEST OCCUPATIONS



SKILLS NEEDED
TO TRANSITION FROM ADMINISTRATIVE EMPLOYEE TO CUSTOMER SERVICE SPECIALIST

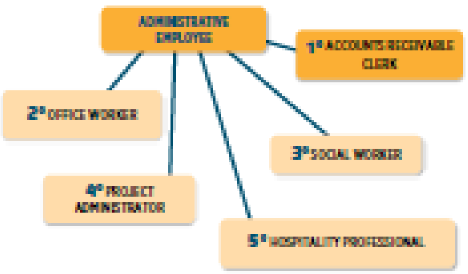
Freight Forwarding	67
International Sales	16
Customs Regulations	15
Project Management Office (Pmo)	11
Service Delivery	7
Pre-Sales	5
Data Center	4
Unix	3
Servers	2
Cisco Systems Products	1

SHARED SKILLS

	ADMINISTRATIVE EMPLOYEE	CUSTOMER SERVICE SPECIALIST
Customer Retention	26	91
Customer Experience	7	73
Shipping	10	53
Organization Skills	72	51
Salesforce.Com	6	30
Sales Operations	6	28
Cold Calling	14	24
Contact Centers	5	24
Interpersonal Relationships	26	21
Freight	3	21

CHILE
ADMINISTRATIVE EMPLOYEE

CLOSEST OCCUPATIONS



SKILLS NEEDED
TO TRANSITION FROM ADMINISTRATIVE EMPLOYEE TO ACCOUNTS RECEIVABLE CLERK

NO ADDITIONAL SKILLS ARE NEEDED TO MAKE THIS TRANSITION

SHARED SKILLS

	ADMINISTRATIVE EMPLOYEE	ACCOUNTS RECEIVABLE CLERK
Administrative Assistance	34	51
Invoicing	28	10
Sap Erp	13	4
Microsoft Outlook	11	9
Purchasing	10	4
Accounting	9	2
Financial Analysis	7	1
Auditing	6	1
Control Theory	6	2
Banking	6	1

POLICY IMPLICATIONS

Download paper at **www.iadb.org/skillsdata**

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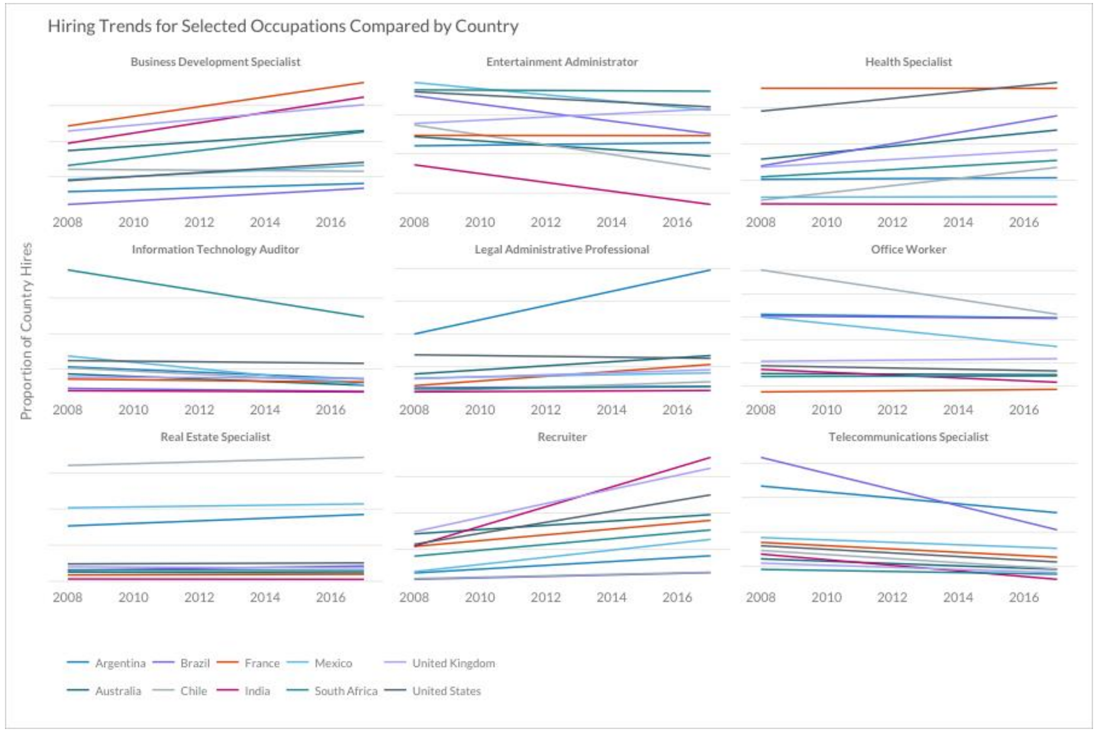
Thank you!

Technical Appendix

Table 1. Definitions and Concepts used in the report

Concept	Definition
Occupation	Members include their job history (positions and roles) as unstructured text. Then, machine learning algorithms categorize these into occupations. LinkedIn has different occupation taxonomies with different levels of granularity. This analysis used a taxonomy of 283 occupations.
Skill	There are three ways to capture skills from LinkedIn member profiles: implicit, inferred, and explicit. Explicit are the skills members confirm or write into their profile. Implicit skills are ones that are extracted from other text in member profiles, but not entered in the skills section (e.g. someone writes "I use Microsoft Office to write legal documents" in the description box for their role). Inferred skills are ones that are inferred based on information in their profile but are not included in the other 2 categories. The analysis in this paper considered implicit and explicit skills. It did not use inferred skills. It also did not consider "endorsements" of skills by other members.
Skill Cluster	LinkedIn has a set of 249 skill clusters. To develop these clusters, team of taxonomists generated a set of cluster names to ensure representation across all industries, functions, and academic/vocational training based on common taxonomies such as ISIC, NAICS O*NET, CIP code and ICBF. An NLP model that uses embedding techniques was run to assign which cluster is 'closest' to each skill. The distance is defined using an embedding space that is developed using co-occurrence of skills. For example, 'C++', 'Java', 'Python', may often appear together on the profiles of software developers and thus they have a close distance to each other. Using the distance measure, 'C++', 'Java', 'Python' could be grouped into the cluster of 'Development Tools'.
Hiring	We looked at member profiles and for each position took the start date as the year of "hire". If a member changes positions but remains with the same employer, this data is not counted as a hire.

Calculating emerging and declining occupations



- For each country and year, hiring for each occupation is measured as a proportion of total hiring for each country-year.
- We estimated a hiring time trend for each occupation-country combination in the period 2008- 2017.
- We used a linear model to regress the hiring rate on a year variable to identify the linear trend of hiring to smooth yearly variation.
- We then ranked all occupations according to their hiring trends to pick the top ten emerging and declining occupations according to this metric.

Calculating changes in skill demand

$$N_{ikt} \equiv N_{ikt} \quad (1)$$

$$N_{ikt} \equiv \frac{N_{ikt}}{N_{it}} * N_{it} \quad (2)$$

$$\sum_i N_{ikt} \equiv \sum_i \frac{N_{ikt}}{N_{it}} * N_{it} \quad (3)$$

$$\sum_i N_{ikt} = \sum_i S_{ikt} * N_{it} \quad (4)$$

$$where\ S_{ikt} = \frac{N_{ikt}}{N_{it}}$$

$$N_{kt} = \sum_i S_{ikt} * N_{it} \quad (5)$$

$$H_{kt_1} = \sum_i S_{ikt_1} * H_{it_1} \quad (6)$$

$$where\ H_{kt_1} = \frac{\Delta N_{kt}}{\Delta N_t}\ and\ H_{kt_1} = \frac{\Delta N_{it}}{\Delta N_t}$$

$$\Delta H_{k\tau} = \sum_i S_{ikt_1} * \Delta H_{i\tau} + \sum_i \Delta S_{ik\tau} * H_{it_1} \quad (7)$$

- Step (1) is an identity. In step (2) we multiply and divide by the number of workers in occupation i. In step (3) we add across all occupations on both sides of the equation. In step (4) use the definition for the share of workers in occupation i who have skill k. In step (5) we use the fact that adding across occupations, provides the total number of workers with skill k.
- In step (6) we fix the moment at which the share of workers in occupation i with skill k is measured and express equation (5) as the hiring rate within that period. The hiring rate is defined as the change in employment in an occupation (or a given skill) as a fraction of the total change in employments within that period. Finally, in step (7) we express the change in the hiring rates as the total (discrete) differential. The changes are computed between the periods τ and t1. The first part is the between component and the second is the within component.

Constructing the occupation-skills network graphs

- We estimate the **importance** of a skill in an occupation by measuring how much higher is the **share of LinkedIn members** who possess that skill in that given **occupation** relative **to the average share** of members who possess that skill in each **country**.
- Based on these measures, we characterize each occupation by a set of **skill importance indexes** and estimate proximity between occupations by calculating the correlation coefficients for every pair of occupations in each country.
- We only kept the **correlation** coefficients which were **statistically significant**. The result is a **matrix** relating every occupation to every other in each of the 10 countries in our sample. We then treated **correlations as distance** measures to be represented in a network graph.
- **Higher** values of **correlations** represent **shorter** distances while lower correlations values represent longer ones. The **nodes** in each graph are the **occupations**, while the **edges** represent the **correlation** between occupations. For visualization purposes we kept **correlations** that had a value of at least **0.5**.

Network statistics

Country	Argentina	Australia	Brazil	Chile	France	India	Mexico	South Africa	UK	US
Occupations (Nodes)	166	229	206	170	228	226	192	196	244	263
Connections (Edges)	267	449	387	341	378	446	413	338	575	960
Connections per Occupation	1.6	2.0	1.9	2.0	1.7	2.0	2.2	1.7	2.4	3.7

Table 2. Network statistics

Note: All networks graphs are undirected, constructed using statistically significant pairwise correlations above 0.5 between all occupations. Edge distance represents the value of each pairwise correlation.

- In Table 2, The United States has, on average, 3.7 related occupations for every occupation while Argentina has 1.6, indicating that the degree of similarity between occupations appears to be higher in the former.

Policy Implications and Recommendations

- **New sources of large-scale data provide timely and granular labor market information that is highly relevant for policy.**
- As a final reflection, these results also show the desirability and usefulness of investing in the infrastructure to make new sources of data interoperable, shared across government agencies, and complementary to traditional sources of information.
- Modern labor market information systems that emphasize integration and interoperability are necessary to facilitate the sharing and dissemination of different sources and types of data to generate a more complete and timely picture of the labor market.
- This intelligence can be shared with a range of stakeholders, including parents and students, workers, employers, policymakers, and education and training providers.