Linkedin Economic Graph

TECHNICAL NOTE

Country-Occupation Skills Mismatch

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Introduction

Skills mismatches – where the skills workers possess do not align with those demanded by employers – lead to productivity losses, slower economic growth, hiring challenges, and missed opportunities for both individuals and businesses[1]. As jobs and required skills evolve rapidly, this challenge is becoming more urgent, and it is critical to identify where the largest skill mismatches exist to better inform upskilling and reskilling strategies.

Understanding where and how these mismatches occur is crucial for:

- **Job seekers**, who need to know which skills will make them competitive
- **Employers**, who want to hire effectively from the available talent pool
- **Educators**, who must train people for real-world demand
- **Policymakers**, who aim to close gaps in the labor market and guide reskilling initiatives

To address this challenge, the Economic Graph Research & Insights (EGRI) team developed a methodology we call the **Skills Mismatch Score**. It measures how aligned employers and workers are – by comparing the skills that show up in job postings to those that appear on member profiles.

[1] Velciu, M. (2017). *Job Mismatch – Effects on Work Productivity. SEA – Practical Application of Science*, Volume V, Issue 15(3), pp. 395–398.
https://seaopenresearch.eu/Journals/articles/SPAS_15_9.pdf

Methodology

The Skills Mismatch Score captures how closely the supply of skills from workers aligns with the skills demanded by employers. By quantifying the gap between what's listed in job postings and what's found in member profiles, the score provides a structured way to identify where skill shortages or surpluses may exist at the country-occupation level.

Our methodology has three steps:

1. Extract demand and supply of every skill, for every occupation. Skills demand is represented by skills extracted from job posts, while skills supply is represented by skills extracted from members' profiles.
2. Apply filtering and winsorization to set minimum thresholds and retain relevant skills for each occupation.
3. Calculate a weighted Skill Mismatch Score that places greater emphasis on skills that are more relevant to the occupation.

We use this methodology to answer two questions:

- What skills are in shortage or surplus for a given occupation in a country?
- How misaligned is an occupation in one country compared to others?

1. Skill-Level Mismatches: What skills are in shortage or surplus?

We calculate a **Skill Mismatch Score** for each skill i, in country c, occupation o, and year y. It reflects two factors:

- The gap between how frequently the skill appears in job postings (demand) vs. member profiles (supply).
- The relevance that skill to the occupation, based on its TF-IDF importance.

$$Skill\ Mismatch, SM_{i,c,o,y} = \frac{w(u_{i,c,o}) \cdot (R^D_{i,c,o,y} - R^S_{i,c,o,y})}{\sum w(u_{i,c,o})}$$

Where:

- $R^D_{i,c,o,y}$= relative demand: frequency of skill *i* in job postings
- $R^S_{i,c,o,y}$= relative supply: frequency of skill *i* in member profiles
- $u_{i,c,o}$= *normalized* TF-IDF rank of skill *i*, calculated as:

$$u_{i,c,o} = \frac{R^{tfidf}_{i,c,o} - 1}{K - 1}$$

  - $R^{tfidf}_{i,c,o}$ = rank of skill i by TF-IDF importance in occupation o in country c

- K = total number of skills considered per occupation

To ensure that low-relevance skills do not distort the score, we apply a weight *w*:

$$w(u_{i,c,o}) = \begin{Bmatrix} 1 - u_{i,c,o}^2 \; if \; u_{i,c,o} < 1 \\ 0 \; otherwise \end{Bmatrix}$$

This weighting function downweights skills with low importance (i.e. high TF-IDF rank numbers), ensuring the mismatch signal is driven by the most relevant skills.,

A large positive Skill Mismatch Score suggests a shortage of an important skill, whereas a large negative score suggests a surplus.

For example, in APAC, there appears to be a potential shortage of full-stack software engineers with infrastructure-related skills such as Kubernetes and Apache Kafka. In contrast, there is a potential surplus of front-end engineers equipped with general programming skills like React.js and Node.js. Refer to Table 1 for a list of software engineering skill mismatches across APAC countries.

Table 1. Skills Mismatch for Software Engineers in APAC countries

Country	Potential skill shortages	Potential skill surpluses
Australia	1. Kubernetes 2. Full-Stack Development 3. DevOps 4. Apache Kafka 5. Test-Driven Development	1. React.js 2. .NET Framework 3. Node.js 4. SQL 5. Python
India	1. Kubernetes 2. Full-Stack Development 3. Apache Kafka 4. Microsoft Azure 5. Microservices	1. HTML 2. Node.js 3. C++ 4. React.js 5. C#
Indonesia	1. Spring Framework 2. Microservices 3. Kubernetes 4. Spring Boot 5. Full-Stack Development	1. Web Development 2. HTML 3. Node.js 4. CSS 5. React.js
Malaysia	1. Spring Framework 2. Microservices 3. Kubernetes 4. Full-Stack Development 5. Spring Boot	1. CSS 2. HTML 3. C++ 4. Node.js 5. TypeScript

Philippines	1. Microservices 2. Spring Framework 3. Spring Boot 4. Full-Stack Development 5. Microsoft Azure	1. CSS 2. HTML 3. Node.js 4. C# 5. React.js
Singapore	1. Full-Stack Development 2. DevOps 3. Microservices 4. Redis 5. Kubernetes	1. Node.js 2. React.js 3. Linux 4. C# 5. TypeScript

2. Occupation-Level Indices: How misaligned is an occupation across countries?

Once we've pinpointed which skills are out of sync within a role, a natural follow-up for policymakers and workforce planners is: **"How severe is the overall shortage or surplus for this occupation?"**

To help answer that, we calculate the **Occupation-Level Mismatch Indices**, which aggregate mismatch scores across all skills within an occupation in a given country. This gives a directional summary of how far employer demand and worker supply are diverging at the occupation level.

$$Shortage\ Index_{c,o,y} = mean(\{SM_{i,c,o,y} \mid SM_{i,c,o,y} > 0\})$$

$$Surplus\ Index_{c,o,y} = mean(\{SM_{i,c,o,y} \mid SM_{i,c,o,y} < 0\})$$

These indices represent the average directional misalignment of skills for that role in a given country.

For example, Investment Analysts in Singapore face a more pronounced skill shortage than their global peers, with an occupation-level shortage index approximately 1.18× higher than the global median for the same role. This elevated demand is driven by skills such as Quantitative Analytics, Trading, and Investment Banking.

In contrast, Data Scientists in Singapore experience a milder shortage, with an index around 0.81× the global median. While there is still unmet demand, the overall gap is less severe, with shortages concentrated in areas like Image Processing, Programming, and Computer Science.

Discussion: Overall, how aligned is a country's workforce?

To begin answering this question, we propose a method to summarize skill mismatches across the entire labor force by aggregating occupation-level mismatch scores into a **Country-Level Mismatch Index**. This index is calculated as a member-weighted average of occupation-specific shortage and surplus scores, offering a high-level view of how closely a country's workforce is aligned with employer demand.

$$Shortage\ Index_{c,y} = \frac{\sum_{o \in O_{c,y}} Member\ Count_{c,o,y} \cdot Shortage\ Index_{c,o,y}}{\sum_{o \in O_{c,y}} Member\ Count_{c,o,y}}$$

$$Surplus\ Index_{c,y} = \frac{\sum_{o \in O_{c,y}} Member\ Count_{c,o,y} \cdot Surplus\ Index_{c,o,y}}{\sum_{o \in O_{c,y}} Member\ Count_{c,o,y}}$$

It is important to note, however, that his approach treats each occupation independently and does not account for cross-occupation substitution effects. That is, situations where workers in one role may possess skills that are in shortage in another role. For instance, if "data mining" is in shortage among Data Analysts but in surplus among Data Scientists, it is theoretically possible that Data Scientists could help fill this gap. However, such movement is rarely seamless in the short term. Factors such as required retraining, job title expectations, hiring practices, and personal career preferences all introduce friction that can limit real-world mobility.

With these caveats in mind, the country-level indices should be viewed as indicators of within-occupation mismatches, not as comprehensive reflections of national skill equilibrium.

If researchers are interested in modelling cross-occupation mobility, a different approach would be needed, one that incorporates the likelihood of skill transfer or movement between occupational pairs. For example, a transition from Data Scientist to Data Analyst may be more plausible than one from Data Scientist to Surgeon, and such variation would need to be explicitly modelled to better account for workforce fluidity.

Conclusion

The Skills Mismatch framework offers a structured and scalable way to understand how well the supply of skills aligns with employer demand. By factoring in rank-based mismatch with skill importance, we focus attention on the most meaningful misalignments in the workforce. While the approach does not capture every possible labor market dynamic, it offers a powerful starting point for identifying where upskilling and reskilling efforts may have the greatest impact. Users are encouraged to use insights from the Skills Mismatch framework as a directional guide for skills mismatch trends, and to combine these insights with other sources of data when conducting workforce planning and policy design.

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