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World of Labor
Evidence-based policy making

Rethinking the skills gap

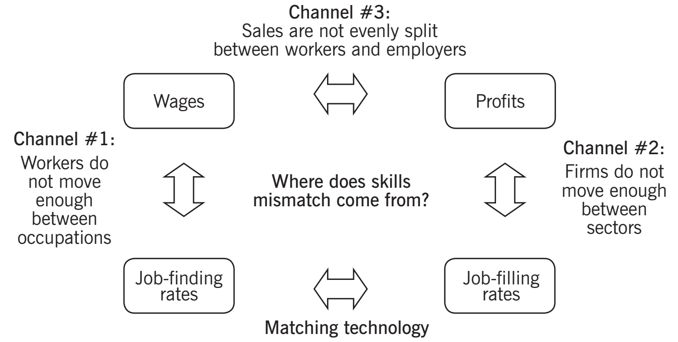
Better understanding of skills mismatch is essential to finding effective policy options

Keywords: skills mismatch, misallocation, productivity, unemployment, wage setting

ELEVATOR PITCH

Evidence suggests that productivity would be much higher and unemployment much lower if the supply of and demand for skills were better matched. As a result, skills mismatch between workers (supply) and jobs (demand) commands the ongoing attention of policymakers in many countries. Policies intended to address the persistence of skills mismatch focus on the supply side of the issue by emphasizing worker education and training. However, the role of the demand side, that is, employers' rigid skill requirements, garners comparatively little policy attention.

Decomposition of the potential sources of skills mismatch



Source: Adapted from [1].

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KEY FINDINGS

Pros

- Analysis shows that 4% of workers are under-skilled, and 11% are over-skilled for their jobs.
- Mismatch is an important determinant of productivity and wages.
- The harmful effect on wages of being mismatched early in one's career is large and persistent.
- Joblessness in an economic downturn would affect one-third fewer people if the mismatch problem was resolved.

Cons

- Though reliable estimates show that skills mismatch lowers individual workers' productivity, effects on aggregate productivity remain largely speculative.
- Estimates of the effect of skills mismatch on unemployment suffer from serious measurement issues.
- Recent literature indicates that focusing on education and training to boost worker skills may be misguided; rather, firms' situations (e.g. being unable to substitute a niche job with positions that are easier to fill) may be a key determinant of skill mismatch.
- US evidence shows that geographic mismatch has a negligible effect on productivity and unemployment.

AUTHOR'S MAIN MESSAGE

Skills mismatch has large effects on productivity and unemployment, and is therefore an important concern for economic policymakers. Almost all proposed policy interventions suggest reforms of education and training as solutions to perceived shortages of skills, while little attention is paid to the rigidity in employers' job requirements. This is problematic because such reforms, which are often expensive, will be ineffective if employers are over-screening candidates, even when skill supply is abundant. If mismatch instead reflects a restrictive recruitment process, then such barriers of entry for workers will prevent them from getting hired even when they have the right skills.

MOTIVATION

The idea that the labor market suffers from severe imbalances in terms of skills offered by workers and those required by employers is a pervasive one. Skills mismatch is viewed as a structural issue—that is, an issue that is present whether the economy is in good shape or in crisis. However, its salience re-emerges during recessions. During the Great Recession, for example, questions arose about whether increased mismatch was the reason that unemployment remained high long after the initial, precipitating events. The recent COVID-19 pandemic also generated concerns about whether job demand shifting towards high-skill remote work would further worsen the prospects of the unemployed who lost their job due to lockdowns. In government circles, the issue is perceived as independent of business cycles. It is not uncommon for some sectors to complain about the trouble they experience finding workers, while unemployment rates remain stubbornly high.

As shown in the illustration on p. 1, three possible reasons could explain why a skills gap persists: (i) workers do not adjust to changes in skills demand by acquiring the new skills needed to find a job; (ii) firms do not adjust to changes in skills supply by creating jobs that utilize the skills available in the labor market; or, (iii) wages do not create enough incentives for workers to acquire scarce skills, or to abandon other occupations.

An important component of the EU's strategic framework for education policy, for example, aims "to better identify and manage the availability of required skills, competences, and qualifications, and to help prevent skills gaps and mismatches." Facing challenges imposed by climate change and the recent pandemic, the EU rolled out an updated version of the European Skills Agenda in 2020. This five-year plan aims to assist workers to "acquire new skills and move to new jobs in a different sector", as well as "to upskill to keep their job in a new work environment". Concerns often focus on shortages of workers with skills in science, technology, engineering, and mathematics (STEM) subjects, but, increasingly, concerns also extend to "soft skills," such as communication, teamwork, and problem solving.

At the same time, many academic economists remain unconvinced of the existence of a skills gap. Accustomed to the idea of the "invisible hand" equating supply and demand, they are naturally skeptical about the idea that large segments of the labor market would persistently be in disequilibrium; that is, they find it hard to believe that job seekers would not adjust to, or acquire the needed skills to work for employers who are willing to offer higher wages.

DISCUSSION OF PROS AND CONS

Researchers have begun to examine issues related to skills mismatch in greater detail and in new ways. The availability of large data sets containing information about workers and firms has made it possible to gauge the effect of skills mismatch on workers' productivity and aggregate unemployment. The literature has also started to explore the causes of mismatch, suggesting policies that may or may not be effective in addressing the issue.

Workers and jobs: Skills mismatch and productivity

The most immediate problem associated with mismatch concerns its effect on productivity. The literature studying this effect looks at existing matches of workers and jobs and tries to determine the extent to which workers have adequate skills to perform their jobs. This issue has two sides: Over- or under-qualification (also called vertical mismatch) occurs when workers have the right type of skills, but are too skilled or not skilled enough. Think of, in the over-skilled category, a linguist teaching a Spanish class, or, in the under-skilled category, a mechanic working as an engineer. Horizontal mismatch (also called field-of-study mismatch) occurs when workers do not have the type of skills required by the job, but they have other skills at a similar level—such as a biology teacher taking over physics classes.

The early literature on mismatch used self-reported data generated from workers' responses to questions about whether they felt under- or over-qualified for their job. A limitation of this approach is that self-reported questions capture workers' under- or over-confidence at the same time as potential mismatch. Beginning in 2011, the OECD's Program for the International Assessment of Adult Competencies (PIAAC) began its Survey of Adult Skills, an assessment designed to provide representative data on workers' skills. The survey delivered an innovation by producing data involving skill proficiencies that are assessed, rather than self-declared. As of 2019, the data include skill measurements of 250,000 individuals in 39 countries.

For each occupation and country included in the PIAAC data, researchers determine a range of skill proficiencies based on the minimum and maximum proficiencies of workers who have defined themselves as being well-matched to their positions. A worker is defined as over-skilled if their skill proficiency is higher than this maximum, under-skilled when their skill proficiency is lower than the minimum. In the latest report from 2019, the OCED researchers find that about 35% of workers in OECD countries are mismatched by qualifications, in which 22% are over-qualified, and 12% are under-qualified [2].

Some researchers provide evidence beyond developed countries using the International Labour Organization's (ILO) ILOSTAT database of "Education and Mismatch Indicators" [3]. Based on the survey data collected from 130 countries, the ILO finds that on average over-education affects 16% of all workers worldwide, and under-education about 37%. In particular, under-education is much more serious in low-income countries, with as many as 70% of workers requiring higher qualifications for their jobs. Hence, while overqualification seems to be a more prominent issue in developed countries, under-education is a critical problem for lower-income countries.

A framework developed in 2015 analyzes worker−occupation matches [4]. If a worker does not possess the abilities that are necessary to learn the skills required by an occupation, then they are "mismatched." Estimating a structural model on US data, the study finds that being mismatched early in one's career harms a worker's wages in a large and persistent manner.

An impressive data set created by the US Department of Labor allows researcher to study mismatches beyond the scope of occupations. It is called O*NET OnLine, and provides a detailed mapping between six-digit Standard Occupational Classification (SOC) codes, occupations, and the usual tasks and skill requirements associated with jobs in each occupation. O*NET data has enabled researchers to measure multidimensional skills, an important improvement over the scalar measure from the PIAAC data. A recent study utilized the O*NET data and finds that the cost of mismatch, measured in loss of production output and disutility of being under-matched, varies across manual, cognitive and interpersonal skills. In general, being mismatched in cognitive skills is more costly than in other skills. Also, this cost is asymmetric as being under-qualified is twice as costly as being over-qualified [5]. It is important to note, however, that not only under-skilled workers would cause output loss. Hiring an overqualified worker would also incur an opportunity cost, since the worker is not utilizing her full productivity. This would also hamper outputs relative to the optimal level.

Quantifying the effect of the overall level of labor market mismatch is much more difficult than measuring the effect of being mismatched on the productivity of individual workers. By combining the multidimensional skill framework with incomplete information on workers' skills, a recent study estimates the output gap associated with skill mismatch to be about 7% throughout a business cycle in the US [6].

Job seekers and vacancies: Skills mismatch and unemployment

If the skills that firms require and the skills that workers possess are sufficiently far apart, then at least some workers will not be hired. Therefore, skills mismatch generates not only a productivity loss, but unemployment as well. Unemployment carries with it huge economic and personal costs. Hence, understanding the effect of skills mismatch on unemployment is important for crafting effective policy.

Labor market mismatch generates unemployment if the unemployed job seekers and firms with vacant positions cannot form a match because the worker and vacancies are "not right" for each other. This idea can be formalized by modeling the labor market as being divided into segments, with workers (and vacancies) unable to move from one labor market segment to another. If there are deviations between the distributions of workers and jobs among the various segments of the labor market, then some workers will remain unemployed while, at the same time, some firms will not be able to fill all positions.

If unemployment is caused by mismatch, then there is a tight link between the dispersion in labor market conditions across labor market segments and the aggregate unemployment rate. The idea is that if there are jobs available in occupations with certain skill sets while unemployed workers are available with different skill sets, then one should see large differences in the ratio of vacancies over unemployment across occupations with different skill requirements. This prediction allows empirical researchers to quantify the aggregate effect of mismatch on unemployment. The challenge is to measure how much lower the unemployment rate would be if—hypothetically, of course—it was possible to reallocate unemployed workers to those occupations where they are most likely to find jobs.

Despite severe measurement issues, there is remarkable consensus in the literature on some basic facts about unemployment due to labor market mismatch. This consensus can be summarized around three main findings: first, that geographic mismatch is negligibly small; second, that skills mismatch, as measured by mismatch across occupations or industries, is an important contributor to unemployment; and third, that skills mismatch is larger during recessions.

The (non)importance of geographic mismatch

A study from 2014 finds that mismatch across US counties and metropolitan statistical areas contributed less than half a percentage point to unemployment—and that this contribution did not rise notably in the Great Recession [7]. The authors thus conclude that "geographic mismatch plays no apparent role [in the unemployment rate]" [7, p.

3529]. This finding is confirmed in a subsequent analysis, which accounts for the fact that workers are not stuck in their counties or states: they look for jobs not only where they live but also in surrounding areas [9]. This is also consistent with evidence showing that geographic (inter-state) mobility did not decrease during the Great Recession. Therefore, geographic mismatch is unlikely to have contributed much to the very large increase in unemployment during this recession.

A study investigates this phenomenon in greater detail by measuring the impact of local fiscal policy and transport improvements on neighboring areas to assesses "how local" a given labor market is [10]. Specifically, the authors investigate how far a local stimulus propagates thanks to worker mobility. They estimate the extent to which job seekers tend to apply for jobs that are further away by combining data on flows into and out of unemployment in England and Wales at the census ward level, and a structural model of job searching and matching. Overall, they find little mobility and modest ripple effects of local policies.

Another recent study applies a similar approach to measure mismatch in the US [9]. Instead of specifying the level of analysis ad hoc (states might be too coarse and zip codes too fine), the researchers allow job seekers to apply everywhere. They use data from the website CareerBuilder.com to observe the locations (at the zip code level) of job seekers, vacancies, and applications. They estimate a measure of "distaste for distance," which captures the reluctance of job seekers to apply for vacancies that are far away. They inject this parameter into a model (as in [10]), in which job seekers decide to apply somewhere based on two criteria: (i) the distance to the vacancy, and (ii) how many job seekers compete for a given vacancy. The authors find that ten more miles decreases the probability of applying for a job by around 35%. This information is then used to predict how many matches will result from a given allocation of job seekers across zip codes; the authors draw conclusions about the gulf between a "perfect" situation—one that would maximize the number of hires—and the situation that occurs when taking into account these geographical and competitive realities. Accordingly, the share of unemployment that is due to geographic mismatch is only around 5%. In other words, reassigning workers over space to maximize hiring would only increase the number of hires by 5%. Yet, while average geographical mismatch might be small, a recent study showed that women might be more heavily affected [11]. Due to their heavier caring duties, women are generally less likely to commute long distances for work. As a result, they are more likely to be mismatched, which in turn likely contributes to the gender pay gap.

Skills mismatch and unemployment

Using SOC codes to categorize the nature of certain kinds of work, a 2014 study finds that increased mismatch across three-digit occupations accounted for around 1.5 percentage points (or about one-third) of the increase in unemployment in the US during the Great Recession [7]. Related research shows similar results for the US and the UK.

The COVID-19 pandemic caused massive disruptions to economic activities. The labor market was no exception, as workers and firms adopted different job search approaches in response to the adverse shock. A recent study documented the change in job search behavior during the early stage of the outbreak using Sweden online job board data [8]. The authors found a massive decline of 40% in new vacancy postings three months into the pandemic. At the same time, however, workers also endogenously adjusted their search behavior towards less-affected occupations.

As the world is coming out of the COVID-19 pandemic, developed countries such as the US and UK have experienced a persistently high vacancy rate. For instance, the US vacancy rate since late 2021 has been about double the post-war average. Meanwhile, according to the findings of a recent briefing note by the Institute for Fiscal Studies, the UK job posting level has been 20 percent above pre-pandemic levels since 2021 [12]. Most of these additional unfilled vacancies are concentrated in lower-skilled and lower-paid occupations, including warehouse workers and truck drivers. This abnormally high vacancy rate can partly be due to an increase in mismatch in the labor market as the economy gradually opens again. However, whether this labor shortage is a part of the transitory process from pandemic lockdowns, or if it is evolving into the "new normal" is as yet unknown.

Understanding occupational codes

Countries usually have a classification system that help classify workers into different occupations. In the US and UK, it is called Standard Occupational Classification (SOC) system. In the case of the US, the two-digit level separates 23 occupations, the three-digit level 97 occupations, the five-digit level 460 occupations, and the six-digit level 840 occupations. For instance, 25–0000 represents education occupations, 25–1000 post-secondary teachers, 25–1050 physical science teachers in post-secondary education, and 25–1052 chemistry teachers in post-secondary education.

The cyclicality of skills mismatch

Using data from 1979 to 2010, evidence suggests that overall mismatch unemployment in the US rose during the recession and fell in good times. This implies the series evolved over time in a very similar fashion to the overall unemployment rate [1]. A similar pattern was revealed using the 2001–2012 sample [7]. These results imply that the rise in mismatch unemployment is not a result of structural transformation in the labor market.

A recent study broke down the cyclicality of mismatch in employment into a "sullying" effect and a "cleansing" effect, which work in opposite directions [6]. The sullying effect increases mismatch at work, as some unemployed workers would need to search for jobs that they might not be best fitted to during a recession. This is essentially the countercyclical components measured by previous studies on mismatch unemployment. Meanwhile, the cleansing effect refers to job separations of marginally mismatched workers, who would not have left their jobs in normal times. This effect reduces mismatch in recessions and is procyclical. The study shows that the cleansing effect dominates and the overall skill mismatch is procyclical. In other words, while mismatch unemployment is countercyclical, when also considering mismatch among employed workers, total skill mismatch is reduced during a recession.

The causes of skills mismatch and how to address them

Unexpected events or phenomena may affect occupations in different ways. A seminal study in 2003 illustrated that the emergence of computers and information technologies reduced the demand for routine jobs and increased the demand for non-routine jobs, which proved to be relatively complementary to the computer [13]. Since then, much effort has been devoted to examining the effect of automations on employment and mismatch.

While machines might be able to replace some tasks, many argue that they would also lead to the creation of other tasks. For example, one recent study examined the emergence of new tasks in the US between 1940 and 2018 [14]. By categorizing patents into "augmentation innovation", which complements labor productivities, and "automation innovations", which only directly enhance machinery efficiency, the authors found that occupations that were exposed to more augmentation advancements introduced more new jobs titles; while automation did not have such positive impact.

With these changes occurring frequently, the fact that mismatch arises is not in itself surprising. The relevant question is: why does it seem to be so persistent?

Why does mismatch persist?

Workers who work (or look for a job) in an occupation where the number of workers exceeds the number of positions have ways to adjust. They can apply to other higher-demand occupations that require similar skills, or they can acquire new skills through training. Alternatively, employers could adjust to workforce shortages by changing the skill content of occupations, or by training up workers from similar occupations to fit new skill requirements.

Adjustment, whether by workers or employers, may be difficult and costly to achieve in the short term, especially when confronting large skill differences between origin and target occupations. Most policy interventions are based on the implicit assumption that this is the reason for the skills gap. The European Commission, for instance, believes that "Europe needs a radical rethink on how education and training systems can deliver the skills needed by the labor market." As a result, it set up the Rethinking Education initiative "to reform education systems across the EU so as to meet growing demand for higher skills levels and reduce unemployment."

A recent analysis uses data on wages and profits across industries in addition to data on job-finding rates to show that it is possible to quantify how much mismatched unemployment stems from a lack of adjustment by workers or from a lack of adjustment by firms. On the workers' side, the following scenario is identified: There are industries where workers have a hard time finding jobs, but where they earn high wages if they do; and there are other industries where jobs are plentiful, but wages are low. This is what one would expect to see if workers operate along a "no arbitrage" condition. That is, if they can move between industries, but will only do so if they are given the right incentives. If, on the other hand, there are many industries where both job-finding rates and wages are high, and others where both are low, the logical conclusion would be that mismatch persists because workers lack the skills required to move into better jobs. Using data for the US from 1979–2010, the study finds that mismatch cannot be fully explained by barriers faced by workers attempting to adjust to changes in skills demand. In addition, it shows that mismatch is not primarily due to employers being unable to pay enough to attract more job seekers to their fields [1].

This then raises the question: If workers adjust to changes in skills demand, and employers try hard to attract workers by offering high wages, how can mismatch persist? The answer lies in the inability of employers to substitute a job position which is hard to fill with one that is easier to fill. One potential reason for such rigidity is because these job positions are perceived as critical to the employers' overall production process. Hence, their function "cannot" be easily replaced by another set of skills. While some unfilled vacancies are indeed non-substitutable in the production process, others might be a result of employers over-screening candidates. For instance, if an organization was trying to hire junior staff, but it requires applicants to have a minimum tenure of related experience, this would contribute to mismatch unemployment. As another example, it would also cause mismatch if a high school was trying to fill a math teacher position, but exclusively considered candidates with math degrees, whereas candidates with other backgrounds, such as accounting or another science degree, should also be capable of performing such a job.

Other researchers, based on very different approaches, have also emphasized the role of recruitment friction. Among the forces suggested to be at work are: automated screening systems that rule out potential candidates who might have surfaced in subjective, human resources screening processes; and a preference for hiring experienced candidates over investing in training for inexperienced but promising candidates. If workers do not move into low-unemployment occupations, the problem may be that some specific job requirements exclude them from consideration.

Apart from these fundamental forces, one of the hottest topics is the rapid development of artificial intelligence (AI) over the past decade and its impact on labor demand. By looking at online vacancy data from 2010 to 2018 in the US, a group of researchers finds that although AI is substituting some comparable human tasks, it has no detectable aggregate labor market effect on employment and wages [15]. However, it is too early to tell the long-term impacts of AI due to its relative newness.

LIMITATIONS AND GAPS

While the literature has progressed during the past decade when it comes to measuring the extent of mismatch and how it affects unemployment and productivity, many measurement-related issues still raise concerns. Potentially, these issues are large enough to affect the qualitative conclusions drawn in this article.

The concept of skills is multi-dimensional, including the amount and quality of education, field of study, and experience in current and previous jobs. Additionally, there are many sorts of skills: technical skills, cognitive skills, soft skills (such as communications, problem solving, the ability to work well in teams), and perhaps even having certain personality traits. Moreover, the extent to which skills are transferable varies. Some skills are general; others are entirely job specific. An ideal data set would account for this broad range of factors and detail the precise set of skill requirements for the job, as well as the precise skill set of the worker. The studies described in this article differ in the ways they address this measurement issue. As a result, it is difficult to pinpoint a "consensus estimate" of the effect of skills mismatch on productivity. The measurement problem is made even more difficult if one tries to estimate the effect of overall mismatch on aggregate productivity, rather than just the effect of being mismatched on an individual worker's productivity.

In the literature on mismatch and unemployment, the measurement issue takes a different form. Here, researchers think of the labor market as being segmented into submarkets, and the primary difficulty with measuring the effects of mismatch lies in finding the correct partitioning of the labor market. Ideally, the partition satisfies two properties. First, submarkets must be closed: No job seeker should end up finding a vacancy in a different submarket than her own. This means that the empirical definition of a submarket should be coarse enough to accommodate some degree of labor market mobility. The second property is homogeneity: Two job seekers (or two vacancies) should be close enough that they can be considered identical by employers (or workers). This means that the definition of segments should be sufficiently precise, otherwise the measure of mismatch will underestimate the true phenomenon. If submarkets are too small, mismatch may be overestimated. So, what is the right partitioning of the labor market? This question first arose in the literature on geographic mismatch, where the submarkets are geographic areas. As discussed previously, accounting for the interconnection between geographic areas is crucial to correctly estimating the aggregate effect of mismatch.

Measuring skills mismatch suffers from the same dilemma as geographic mismatch in terms of the difficulty in defining sensible submarkets. The SOC, although a detailed and systematic categorization of the nature of different kinds of work, is an imperfect vessel for this analysis. The introduction of O*NET data mitigates parts of this issue by allowing jobs to be characterised by their task contents. Some recent studies mentioned in this article adopt this task-based framework and compute "distances" across occupations by their corresponding difference in skill requirements along multiple dimensions. This allows them to bundle occupations with very different three-digit codes but with similar skill mixes. For instance, according to some methodologies, an economist is considered to share the same market as actuaries, financial managers, and mathematicians and statisticians. Although one can easily pin-point the common features of these occupations, whether workers can indeed easily transfer between them is still in doubt. There can be barriers beyond measures of skill sets, such as specific industry know-how, that prevents these cross-occupation transitions.

A separate issue involves the question of what data to use. In the US, job seekers are counted using the Current Population Survey (CPS), which assumes that the industry and occupation of a job seeker are both the same from one job to another. For vacancies, two US data sources are available. The first is the Job Openings and Labor Turnover Survey (JOLTS), which serves as a source of demand-side indicators of labor shortages at the national level, and allows researchers to compute the number of vacancies by industry (at a two-digit SOC level). The second is the Conference Board's Help Wanted OnLine (HWOL), which is made up of the universe of unique online job vacancies in the US; these are collated into counts of vacancies by occupations. These two sources (JOLTS/HWOL) provide the most straightforward measure of the vacancy–unemployment ratio across industries and occupations. Many studies use these sources at the price of working on a relatively short time window [7], [10]. Other studies have to rely on assumptions about the matching technology to compute the vacancy–unemployment ratio from the job-finding probabilities measured in the CPS [1]. This technique results in a much longer time series. Luckily, findings look very similar in research relying on these different sources, lending additional credibility to the results.

However, aggregate vacancy data like JOLTS and HWOL lack detailed task descriptions of jobs and thus suffer the same categorizing issues in defining submarkets. To mitigate this problem, some researchers turn to online job posting data for a more comprehensive description of each vacancy. Examples include Glassdoor and Linkedin. While these datasets provide job descriptions with great details the main issue is that they might not be representative of the whole labor market. These online platforms' job advertisements tend to target certain submarkets only. Lower-skilled jobs, whose candidates might not be frequent users, would likely be omitted. Another issue with these datasets is that many cover only a short period of time.

Finally, when it comes to the causes of mismatch, the evidence is very thin indeed. It should be expected that the thinking on this issue will progress substantially as further research sheds light on the mechanisms and trade-offs behind wage determination.

SUMMARY AND POLICY ADVICE

Skills mismatch is an important cause of productivity loss and unemployment. Thus, policy making tools that diminish its presence and persistence can benefit economies, firms, and people who are unemployed or underemployed.

However, in the context of the European Commission's proposed "radical rethink on how education and training systems can deliver the skills needed by the labor market," a reform of education and training systems may be neither needed nor desired. The most striking conclusion from current research is that worker mobility frictions may not be the main contributor to labor market mismatch. Yet, almost all proposed solutions to the skills gap treat the phenomenon as a problem of the education system. Such interventions in education and training are likely to be expensive, and, at the same time, may not be as effective as expected.

Why would increasing the emphasis on "scarce" skills in schools and universities fail to guarantee that skills mismatch will be reduced? The reason is simply that while students choose what skills to acquire in school and university, it is up to the employers to define the hiring requirements of each job. Hence, whether a student is deemed qualified as a "hirable" candidate is primarily determined by employers. Most hiring criteria not only specify the "range" of skills required, but also the "depth" of skills. Demonstrations of skill depth usually involve either "school grades" or "previous work and internship experience". If job requirements are restrictive, especially along the depth of skill demanded, students with the right skillset but without sufficient depth will be excluded from consideration. Pushing more students to acquire "scarce" skills is likely to produce some elite candidates that will be in high demand, but it will simultaneously generate more "underqualified" candidates who might contribute to greater mismatch. In other words, encouraging universities to educate more physicists and engineers will not solve the mismatch problem if firms are strictly looking for someone with an internship certificate at NASA.

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Competing interests

The IZA World of Labor project is committed to the *IZA Guiding Principles of Research Integrity*. The authors declare to have observed these principles.

REFERENCES

Further reading

Cappelli, P. *Why Good People Can't Get Jobs: The Skills Gap and What Companies Can Do About It*. Philadelphia, PA: Wharton Digital Press, 2012.

Handel, M., A. Valerio, and M. L. Sanchez Puerta. *Accounting for Mismatch in Low- and Middle-Income Countries: Measurement, Magnitudes, and Explanations.* Washington, DC: World Bank Group, 2016.

Key references

[1] Herz, B., and T. van Rens. "Accounting for Mismatch Unemployment." *Journal of the European Economic Association* 18:4 (2020): 1619–1654.

[2] OECD. *Skills Matter: Additional Results from the Survey of Adult Skills.* Paris: OECD Publishing, 2019.

[3] Stoevska, V. "Only half of workers worldwide hold jobs corresponding to their level of education". *ILOSTAT* (2021).

[4] Guvenen, F., B. Kuruscu, S. Tanaka, and D. Wiczer. "Multidimensional Skill Mismatch". *American Economic Journal: Macroeconoimcs* 12:1 (2020): 210–244.

[5] Lise, J., and F. Postel-Vinay. "Multidimensional Skills, Sorting, and Human Capital Accumulation." *American Economic Review* 110:8 (2020): 2328–2376.

[6] Baley, I., A. Figueiredo, and R. Ulbricht. "Mismatch Cycles." *Journal of Political Economy* 130:11 (2022): 2943–2984.

[7] Şahin, A., J. Song, G. Topa, and G. L. Violante. "Mismatch unemployment." *American Economic Review* 104:11 (2014): 3529–3564.

[8] Hensvik, L., T. Le Barbanchon, and R. Rathelot. Job search during the COVID-19 crisis. *Journal of Public Economics* 194 (2021): 104349.

[9] Marinescu, I., and R. Rathelot. "Mismatch unemployment and the geography of job search." *American Economic Journal: Macroeconomics* 10:3 (2018): 42–70.

[10] Manning, A., and B. Petrongolo. "How local are labor markets? Evidence from a spatial job search model." *American Economic Review* 107:10 (2017): 2877–2907.

[11] Petrongolo, B., and M. Ronchi. Gender gaps and the structure of local labor markets. *Labour Economics* 64 (2020): 101819.

[12] Joyce, R., F. Postel-Vinay, P. Spittal and X. Xu. *Job opportunities after the pandemic.* IFS Briefing Note BN342 (2022).

[13] Autor, D., F. Levy, and R. Murnane. "The skill content of recent technological change: An empirical exploration." *Quarterly Journal of Economics* 118:4 (2003): 1279–1333.

[14] Autor, D., C. Chin, A. M. Salomons, and B. Seegmiller. *New Frontiers: The Origins and Content of New Work, 1940–2018.* NBER Working Paper 30389, 2022.

[15] Acemoğlu, D., D. Autor, J. Hazell, and P. Restrepo. Artificial Intelligence and Jobs: Evidence from Online Vacancies. *Journal of Labor Economics* 40:S1 (2022): S293–S340.

Online extras

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