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Assessing Qualification Mismatch in sub-Saharan Africa: Concepts, Indicators, and Data Sources

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Assessing Qualification Mismatch in sub-Saharan Africa:
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Chapter 1
Introduction

'Skills' and 'qualifications' are often interchangeably used in the literature, but they refer to two different concepts. While skills correspond to a larger concept encompassing the knowledge, attributes, and capacities enabling individuals to perform an activity or task (OECD, 2011), qualifications – also termed 'credentials' – refer specifically to the official confirmation, usually in the form of a document, certifying the successful completion of an education programme. Qualifications can also be obtained through validation of acquired knowledge, skills, and competencies, independent of participation in an education programme (UNESCO-UIS, 2012).

Skills (qualifications) mismatch corresponds to a misalignment between the skills (qualifications) demanded in the labour market and the skills (qualifications) possessed by the labour force. It arises, in particular, when the education system fails to supply the skills sought by employers (supply side), or when the economy fails to create jobs that correspond to individuals' skill endowments (demand side).

Empirical studies on skills mismatch are scarce in sub-Saharan Africa due to the lack of adequate data and statistical capacity. However, recent evidence indicates that sub-Saharan Africa along with southern Asia account for the regions most affected by qualification mismatch, mainly as a result of high incidences of under-qualification (ILO, 2019). sub-Saharan Africa stands out as the region with the lowest levels of schooling but the highest returns to education (Psacharopoulos and Patrinos, 2018).

Uncovering the reasons for persistent gaps between the skills demanded and those available is more complex than it appears. Drivers of skills mismatch are multiple and diverse, and can include: limited wage employment opportunities, the crushing weight of the informal economy, the prominence of low-quality jobs, uncompetitive wages, poor recruitment practices, and barriers to geographical mobility. Besides, mega-trends such as demographic changes, globalization and trade liberalization, technological evolution, and climate change can also fuel skills mismatch (ILO, 2019).

Yet, education and training systems struggle – not to say fail – to quickly align with fast-changing labour market needs triggered by interconnected economies constantly in motion. The relevance of skills, including technical and vocational skills, for employment and decent work features prominently in the Sustainable Development Goals (SDG) (target 4.4). Persistent skills gaps and shortages in sub-Saharan Africa prompt heightened efforts towards comprehensive demand-led skills development strategies. In this context, assessing the current and future prospects on the labour market proves to be key for addressing the potential imbalance between the demand for and supply of skills.

The lack of proper and systematic skills needs assessment and anticipation mechanisms is a major hurdle in sub-Saharan Africa's efforts to tackle the skills mismatch challenge. Investing in this domain as part of Labour Market Information Systems (LMIS) is thus crucial to identify policy solutions addressing demand-side and supply-side deficiencies. Policy solutions typically include adapting the curricula and education provision to labour market needs, strengthening work-based learning and, in particular, subsidising the provision of on-the-job training, setting up closer collaborations between the world of work and the education system, and providing better career guidance and advice to students.

Against this backdrop, the present report aims to provide policy makers, development practitioners, and researchers with the necessary tools for analysing qualification mismatches in sub-Saharan Africa. It goes beyond existing frameworks by taking into account data constraints and the labour market context pertaining to the region.

The report adopts a pragmatic approach by focusing on qualifications given the scarcity of available data on skills, and presents a set of key indicators that allow quantitatively assessing qualification mismatches based on the most reliable and representative data commonly collected in sub-Saharan Africa. These indicators have been selected based not only on their relevance and availability in the sub-Saharan African context, but also on their simplicity, which allows countries to compute them easily. The report builds on recommendations from the International Conference of Labour Statisticians (ICLS) and similar exercises conducted in developing countries.

The report is structured as follows: Chapter 2 discusses the concepts and operational definitions for measuring skills, qualifications, qualification mismatches, and other labour market conditions that are strongly correlated. Chapter 3 describes the indicators retained to comprehensively analyse qualification mismatches in sub-Saharan Africa, and provides empirical illustrations based on preliminary analyses conducted in four pilot countries (Benin, Kenya, South Africa, and Uganda). Chapter 4 goes beyond the analysis of qualification mismatches by describing quantitative, qualitative, and mixed methods, as well as big data approaches to assess and anticipate skills needs. As put forward earlier, skills needs assessment and anticipation constitute an integral part of an effective policy response to prevent skills mismatches. Chapter 5 focuses on an inventory of existing data sources in sub-Saharan Africa and discusses their strengths and limitations. Finally, Chapter 6 concludes and recommends a stepwise approach to measuring qualification mismatches.

Chapter 2
Introducing qualification mismatch: Concepts and operational definitions

This chapter first deals with the concepts related to skills and qualifications and then turns to the various forms of qualification mismatch, focusing on operational definitions and measurement approaches. To have a broader picture of qualification mismatches, it is necessary to also account for other labour market conditions that are strongly correlated, in particular labour underutilization and informality. The last section of the chapter introduces the concept of informal employment as well as two common measures of labour underutilization, namely unemployment and time-related underemployment, and documents their links with qualification mismatches. All concepts covered here will be addressed in more detail in the following chapter which digs into a selection of indicators for an exhaustive analysis of qualification mismatches.

2.1 Defining skills and qualifications

There is no uniform definition of 'skills'. For instance, the Organisation for Economic Co-operation and Development (OECD 2011: 7) defines skills as 'the bundle of knowledge, attributes and capacities that enables an individual to successfully and consistently perform an activity or task, and that can be built upon and extended through learning'. Broadly speaking, skills encompass the ability to apply knowledge and are a key predictor of the ability to work. They are often hard to measure. Direct measurement usually involves testing specific skills, which occurs within qualification institutions and more rarely in other contexts. Some international surveys[1] aim to capture different sets of skills, but given their complexity and cost, they are more the exception than the rule in developing countries. Alternatively, subjective approaches to skills measurement consist in directly asking workers and employers about skills held or required in the occupation.[2]

Skills can be proxied by qualifications in the absence of direct measurement, which is typically the case in sub-Saharan Africa, where data on individuals' skills and skills content of jobs are lacking.[3] Qualifications are usually measured in survey data by the highest level and field of completed education based on the International Standard Classification of Education (ISCED). Using qualifications as a proxy for skills is not exempt from certain caveats. The education system delivers curricula and tests students' proficiency before granting qualifications. Not all skills envisioned by the education system are necessarily held by graduates. Some of these skills may not be properly covered in the curricula, taught, or tested during qualification exams. Besides, skills acquired outside the education system are not captured by qualifications. That being said, it is routinely assumed that qualifications represent a fixed bundle of skills that each graduate possesses.

1 For instance, the OECD Programme for the International Assessment of Adult Competencies (PIAAC), and the World Bank's Skills towards Employment and Productivity (STEP) Measurement Programme in low-and middle-income countries.

2 Subjective approaches are commonly applied in tracer studies and employer surveys, and aim to inform in particular on skill shortages, staffing problems, and training needs.

3 Recent data collection efforts like the European Skills and Jobs Survey (ESJS) conducted by CEDEFOP attempt to identify and measure skills possessed by individuals and skills requirements of jobs. However, these surveys are quite elaborate and therefore not common in low-and middle-income countries.

2.2 Defining qualification mismatches

Qualification mismatches correspond to misalignments between the qualifications demanded in the labour market and the qualifications possessed by the labour force. They arise in particular when the education system fails to supply the qualifications sought by employers, or when the economy fails to create jobs that correspond to individuals' qualifications. Qualification mismatch can take different forms, which typically include over/under qualification (vertical mismatch) and field of study (horizontal) mismatch. Other forms of mismatch related to skills – i.e., skills gaps, skills shortages, and skills obsolescence[4] – are beyond the scope of the report and, therefore, are not discussed here.

- **Vertical mismatch:** occurs when workers do not have the required level of education to perform the tasks in their occupation. If their level of education is above that required for the job, they are considered over-qualified. Conversely, if their level of education falls below that required for the job, they are considered under-qualified. There are two main approaches to identify the required level of education in the occupation. With the normative method, vertical mismatch – also called occupational mismatch – is based on the occupational skill levels of the International Standard Classification of Occupations (ISCO). By contrast, the empirical method determines the required level of education empirically using the most frequent (mode) level of education of workers in an occupational group. Other methods of measuring vertical mismatch exist. The job evaluation method, which is also normative, relies on experts to assess the educational requirements for an occupation. While more precise, this approach is quite costly to generate and update with changing skill requirements. Finally, the subjective method directly asks respondents to report the level of education or skills required for the job. With this method, results can be biased due to different perceptions among individuals.
- **Horizontal mismatch**: occurs when workers' occupation is unrelated to their field of study. Horizontal mismatch can be determined subjectively, but the most common approach consists in comparing workers' field of study and occupational group. Proper identification of this type of mismatch requires establishing a clear correspondence between the two based on international classifications (ISCED and ISCO).[5] Another limitation lies in that specialisation generally occurs at tertiary education, a level that a minority of students attain in sub-Saharan Africa.

4 Skills gaps arise when workers lack the skills necessary to do their jobs effectively. Skills shortages emerge when vacancies are hard to fill because employers do not find applicants with the right qualifications and skills. Finally, skills obsolescence occurs when workers do not use their skills and ultimately lose them, or when skills acquired become obsolete due to the evolving labour demand. More detailed definitions of skills and qualifications mismatches can be found, for instance, in Quintini (2014), Handel, Valerio, and Sanchez Puerta (2016), ILO (2018a, 2019), and ETF (2012).

5 See Wolbers (2003) and Levels et al. (2014) for cross-country analyses using this approach.

2.3 Defining labour underutilization and informal employment

As mentioned in the introduction, many factors can drive qualification mismatches. The informal economy is the main source of employment in sub-Saharan Africa and, therefore, deserves particular attention. In fact, the sub-Saharan Africa region is hardest hit by informal employment with levels rising to 89.2% overall, and 76.8% when excluding agriculture (ILO, 2018b). The evidence shows that informality is a key determinant of qualification mismatch in low- and middle-income countries, especially for youth; the lack of formal employment opportunities fuels overqualification (see, for instance, ILO, 2019; Handel, Valerio, and Sánchez Puerta, 2016; Herrera and Merceron, 2013). Informal employment can be seen as an alternative to unemployment. When qualified jobs are lacking, educated people either remain unemployed while queuing for formal jobs that better match their qualifications or fall back on informal jobs for which they are over-qualified. In sub-Saharan Africa, widespread poverty and almost non-existent unemployment benefits and other social safety nets make unemployment undesirable for many individuals who end up occupying poor quality jobs in the informal economy. These jobs are typically characterized by low productivity and poor working conditions.

- **Informal employment**: encompasses all remunerative work (i.e. both self-employment and wage employment) that is not registered, regulated or protected by existing legal or regulatory frameworks, as well as non-remunerative work undertaken in an income-producing enterprise (ILO, 2003). The international statistical definition of informal employment is based on the 17th International Conference of Labour Statisticians (ICLS) guidelines, whose contextual framework links the enterprise-based concept of employment in the informal sector in a coherent and consistent manner with a broader, job-based concept of informal employment (ILO, 2013a).

  Following the international statistical definition, all informal workers are considered, irrespective of the type of production units they work in (formal sector enterprises, informal sectors enterprises, and households). Concretely, they are classified as informal all contributing family workers, employees not registered with a social security scheme or not entitled to paid annual leave or paid sick leave, and self-employed workers who do not keep official accounts and whose economic unit is small and not registered under national legislation.

Labour underutilization refers to mismatches between labour supply and demand, which translate to an unmet need for employment among the population (ILO, 2013b). The most widely used measures of labour underutilization are unemployment and time-related underemployment. As discussed above, unemployment and qualification mismatches are intertwined. Causes of unemployment can be many, but when it coexists with job vacancies that remain unfilled, qualification mismatches are often blamed along with other factors like uncompetitive wages, inadequate recruitment practices, and poor working conditions (ILO, 2019). In low-and middle-income countries, overqualification goes hand-in-hand with unemployment because jobseekers compete for a limited number of qualified jobs. Young people are particularly at risk of unemployment and overqualification since the creation of qualified jobs does not keep pace with the increasing number of graduates who enter the labour market.

Besides, protracted unemployment spells reduce the reservation wage as well as the propensity of individuals to apply for jobs they are qualified for (Herrera and Merceron, 2013).

- **Unemployment**: according to the 19thICLS (ILO, 2013b), persons in unemployment are defined as all those of working age who: (i) were not in employment, (ii) carried out activities to seek employment during a specified recent period, and (iii) were currently available to take up employment given a job opportunity. In the context of developing countries where most jobseekers resort to informal channels to find work, a broader definition of unemployment relaxing the job search criterion is generally preferred. This broader definition captures, in particular, discouraged jobseekers who gave up the job search due to the lack of employment opportunities and inadequate skills.

Underemployment reflects underutilization of the productive capacity of the labour force. It comprehends two distinct components: (i) 'visible' underemployment, commonly known as time-related underemployment, which can be measured in terms of hours of work; and (ii) 'invisible' underemployment, which refers to other inadequate employment situations related to income, labour productivity, or skills. Because the latter are harder to quantify, only time-related underemployment benefits from an international statistical definition (ILO, 2013b). In sub-Saharan Africa, since unemployment is undesirable for most individuals and low unemployment levels mask tremendous decent work gaps, it is recommended to extend the analysis of labour underutilization to various forms of underemployment. In fact, the previous section has already dealt with 'invisible' underemployment given that overqualification provides a fair illustration of skills-related inadequate employment. We turn here, therefore, to the 'visible' component and the so-called time-related underemployment.

Persons in employment are considered time-related underemployed when their working time is insufficient in relation to alternative employment situations in which they are willing and available to engage (ILO, 2013b). According to ILO (2021), time-related underemployment is the most widespread form of labour underutilization in sub-Saharan Africa due to the high prevalence of low-productivity work. There is little evidence on the links between time-related underemployment and qualification mismatches. This is due, at least in part, to the difficulty in interpreting time-related underemployment as it constitutes a complementary form of labour underutilization that is defined based on personal assessment. However, ILO (2019) shows, for instance, that underqualification among young workers in low- and middle-income countries is associated, *inter alia*, with involuntary part-time employment.

- **Time-related underemployment**: according to the 19th ICLS (ILO, 2013b), persons in time-related underemployment are defined as all persons in employment who, during a short reference period: (i) wanted to work additional hours, (ii) worked in all jobs less than a specified hours threshold, and (iii) were available to work additional hours given an opportunity for more work. The second criterion is generally based on the statutory working hours for full-time employment according to national legislation.

Chapter 3

Measuring qualification mismatch: Selected indicators

Lack of reliable data and limited research capacity make it difficult to assess qualification mismatches in sub-Saharan Africa. The challenge extends to the need to improve coordination among stakeholders in conducting the analyses and translating the results into adequate policy responses.

The best approach in analysing qualification mismatches consists in using a combination of quantitative and qualitative methods. In this report, we recommend adopting a pragmatic approach by calculating a set of key indicators that allow quantitatively assessing qualification mismatches based on the most common representative data in sub-Saharan Africa, namely labour force surveys (LFS) or household surveys containing an employment module. According to ILO (2018a), these are the most reliable and regularly collected surveys with labour market information. When available, additional data sources can be used to provide a more comprehensive and detailed picture of qualification mismatches (see Chapter 5 for a discussion on existing data sources and their availability in the continent).

Building on recommendations from the International Conference of Labour Statisticians (ICLS) (ILO, 2013b, 2018a), we propose a list of indicators – to be calculated and updated on a regular basis following international statistical standards – that should form the basis of any labour market information system (LMIS). We classify the indicators into two categories: (i) core labour market indicators and (ii) qualification mismatch indicators. The first category comprehends standard labour market indicators on access to employment, labour underutilization, and informality that shed light on potential skills imbalances. The second category focuses directly on qualification mismatches and includes indicators on over/under qualification (vertical mismatch) and field of study (horizontal) mismatch.

The rest of the chapter describes the indicators retained and provides an empirical illustration for each of them based on analyses conducted in four pilot countries (Benin, Kenya, South Africa, and Uganda).[6] Core labour market and qualification mismatch indicators have been selected based not only on their relevance in the sub-Saharan African context, but also on their availability – through representative and reliable surveys – and their simplicity to allow countries computing them easily. Clearly, indicators should be systematically disaggregated according to various socio-demographic factors, such as sex, age cohort, area of residence, educational attainment, and occupational group, to account for population heterogeneity. However, data disaggregation is rendered difficult by the limited number of observations, especially for underrepresented categories of individuals, in nationally-representative household surveys. This is all truer in sub-Saharan Africa, where, for instance, a residual share of individuals attained terminal levels of education, resulting in overly small sample sizes to perform detailed data disaggregation.

6 Pilot countries were selected based on data availability, geographical location, and socio-economic context in order to reflect the diversity of sub-Saharan Africa.

3.1 Core labour market indicators

Labour supply and demand are continuously trying to allocate persons to jobs such that skills and tasks match. While not directly connected to qualification mismatch, workers can experience decent work gaps that, in the context of sub-Saharan Africa, usually take the form of labour underutilization and informal employment. Workers in such situations are assumed to be mismatched in a broader sense as they are confined to less rewarding jobs. With the core labour market indicators, we focus on these two particular labour market conditions that are strongly correlated with qualification mismatch, and that reflect the difficulties of the labour force in accessing employment and occupying quality jobs. We will turn to direct measures of qualification mismatch in the next section.

Core labour market indicators include unemployment and time-related underemployment as the most common measures of labour underutilization, the share of young people not in education, employment, or training (NEET), which can be considered as a broader measure of young labour underutilization, and other well-known indicators – namely, employment-to-population ratio and inactivity rate – that allow providing a more comprehensive picture of access to employment.

3.1.1 Employment-to-population ratio

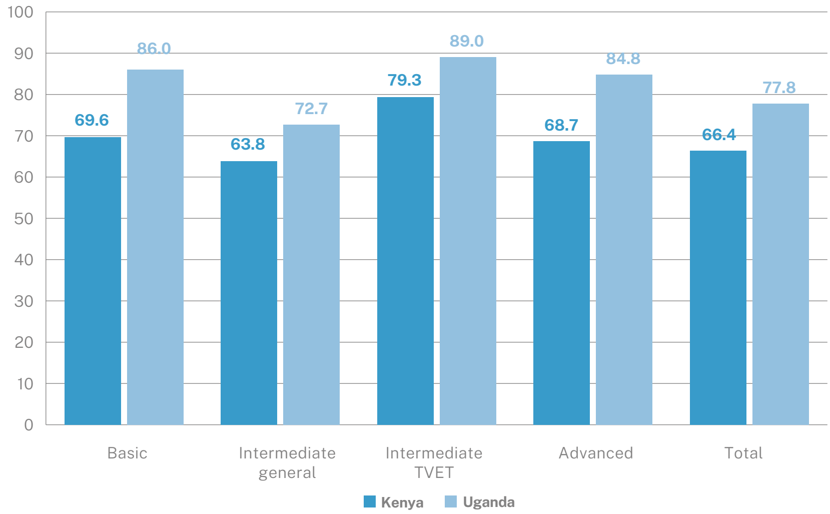
The first step of the analysis consists in determining the labour force status of the working-age population, who can be classified into three mutually exclusive and exhaustive categories: (i) employment, (ii) unemployment, and (iii) out of the labour force, also termed 'inactivity' (ILO, 2013b). These categories are not determined simultaneously but follow a precise sequence. We first identify the employed population and then unemployed workers; these two categories representing the labour force. Inactivity is ultimately defined as a residual comprising all working-age individuals neither employed nor unemployed. We start with employment and address the other labour force statuses in the following sections.

According to the 19th ICLS (ILO, 2013b), persons in employment are defined as all those of working age who, during a short reference period, were engaged in any activity to produce goods or provide services for pay or profit. They comprise employed persons: (i) 'at work', that is, who worked in a job for at least one hour; and (ii) 'not at work' due to temporary absence from a job, or to working-time arrangements (such as shift work, flexitime, and compensatory leave for overtime).

The employment-to-population ratio is the standard indicator for the measurement of employment. Defined as the percentage of employed persons in the working-age population, it corresponds to the first indicator of the substantive element on employment opportunities of the ILO Decent Work Agenda (ILO, 2013c).

As employment opportunities expand, more and more jobseekers find work and the employment-to-population ratio goes up. However, a high ratio or upward trend does not necessarily mean that labour market conditions are good or improving. In sub-Saharan Africa, low educational attainment, lack of social safety nets, and poverty force many individuals to prema-

Figure 1 Employment-to-population ratio by education level in Kenya and Uganda, latest year available



Source: Own calculations based on Uganda Labour Force Survey (LFS) 2018 and Kenya Continuous Household Survey Programme (KCHSP) 2020

Notes: The following aggregate levels of education are considered: (i) Basic (no schooling, early childhood education, primary education, and lower secondary education); (ii) Intermediate (upper secondary education and post-secondary non-tertiary education); (iii) Advanced (short-cycle tertiary education, bachelor's or equivalent level, master's or equivalent level, and doctoral or equivalent level). For intermediate levels, we consider separately general and TVET education.

turely enter the labour market, where they end up holding low quality jobs. Conversely, a low ratio or downward trend indicate that a large or increasing proportion of working-age individuals are unemployed or out of the labour force. This situation can be attributed to the lack of employment opportunities, discouragement among jobseekers who give up the job search, or particular situations – some commendable (e.g. school enrolment, retirement), others not (e.g. illness/disability, binding social and cultural norms, unpaid care work) – that keep individuals economically inactive.

Figure 1 displays the employment-to-population ratio by education level in Kenya and Uganda. In both countries, intermediate TVET education is associated with the highest employment-to-population ratio, and intermediate general education with the lowest. These findings are not surprising since specialised studies in vocational trades are expected to endow individuals with skills and competencies that better speak to labour demand. Further results show that young people and women exhibit disproportionately low levels of employment and, therefore, they are more at risk of unemployment or economic inactivity.

3.1.2 Unemployment rate

Our discussion now turns to the next labour force status, which is measured by the unemployment rate. This indicator is defined as the percentage of unemployed persons in the labour force or, equivalently, the economically active population, which includes both employed and unemployed persons. According to the international statistical definition adopted by the 19th ICLS (ILO, 2013b), unemployment comprises all persons of working age who: (i) were not in employment, (ii) carried out activities to seek employment during a specified recent period, and (iii) were currently available to take up employment given a job opportunity.

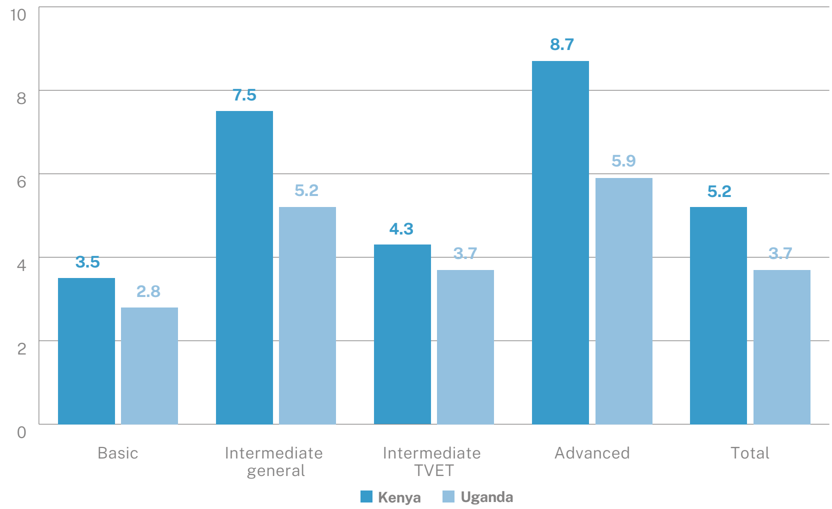
This strict definition of unemployment does not suit well the particular labour market conditions pertaining to sub-Saharan Africa and other developing regions. Widespread poverty, almost inexistent unemployment benefits and other social safety nets, and large informal labour markets dominated by contributing family work and other subsistence activities, render unemployment unaffordable for most individuals, thus explaining the relatively low official unemployment rates observed in sub-Saharan Africa (ILO, 2021; Herrera and Merceron, 2013).

Therefore, in the context of sub-Saharan Africa where most jobseekers resort to informal channels (e.g., family and friends) to find work, a broader definition of unemployment relaxing the job search criterion is generally preferred. The broader definition captures in particular discouraged jobseekers who gave up the job search due to the lack of employment opportunities and inadequate skills.

As already seen, unemployment is a complex phenomenon that can be attributable to multiple factors. Therefore, it should be analysed in conjunction with other indicators, starting with those proposed in this report, to better understand its causes and, in particular, how it relates to qualification mismatches. First of all, unemployment is not necessarily structural as it can result from an economic slowdown or other conjunctural adverse conditions. Weakened aggregated demand slows down job creation or, worse, leads to job destruction, which mechanically drives up the unemployment rate. Accordingly, we can presumably blame qualification mismatches, along with other structural factors such as uncompetitive wages, inadequate recruitment practices, and poor working conditions, for unemployment only when there are vacancies that remain unfilled (ILO, 2019). In developing regions like sub-Saharan Africa, overqualification goes hand-in-hand with unemployment because jobseekers compete for a limited number of qualified jobs.

Given the heterogeneity of the population, individual and household characteristics should be taken into account when analysing unemployment. Since qualification mismatches are our primary focus, we should look first on the unemployment rate by level of education. In sub-Saharan Africa, we commonly observe a positive correlation between unemployment and educational attainment (Herrera and Merceron, 2013). This is because individuals with higher levels of schooling usually come from wealthier families and can more easily afford to remain unemployed while queuing for better jobs.

Figure 2 Unemployment rate by education level in Kenya and Uganda, latest year available



Source: Own calculations based on Uganda Labour Force Survey (LFS) 2018 and Kenya Continuous Household Survey Programme (KCHSP) 2020

Note: Unemployment defined according to the international statistical definition. See the Figure 1 note for the definition of aggregate levels of education.

The analysis of unemployment can be extended to the length of job search. The duration of unemployment corresponds to the time an individual defined as unemployed spent seeking work. Short-term unemployment is often seen as frictional and, to some extent, necessary to allow individuals to move towards new opportunities. Long-term unemployment – usually defined as a job search lasting for a year or longer – hints structural problems in the economy. The longer unemployment lasts, the more skills and knowledge become obsolete, and the harder it becomes for an individual to find suitable employment. In particular, a prolonged period of unemployment reduces the reservation wage and the propensity of individuals to apply for jobs they are qualified for; hence, overqualification constitutes a way out of long-term unemployment (Herrera and Merceron, 2013).

Figure 2 displays the unemployment rate according to the international statistical definition by education level in Kenya and Uganda. In both countries, individuals with advanced studies are the most affected by unemployment, followed by individuals with intermediate general, intermediate TVET, and basic education. These results are in line with previous findings on employment and provide an empirical illustration of the positive correlation between unemployment and educational attainment.

Results can be interpreted as follows: On one hand, uneducated or low-educated people generally cannot afford to remain unemployed and take whatever job they find, usually in the informal economy, to sustain their livelihoods. On the other hand, more educated people can face protracted unemployment spells due to the deficit of qualified jobs. The fact that those with advanced studies are the hardest hit by unemployment suggests that low- and medium-skilled jobs are relatively more abundant than high-skilled jobs in the countries under study. According to OECD (2017), Africa stands out as the region with the largest share of tertiary educated youth engaged in medium- or low-skilled jobs. High-skilled job creation does not keep pace with the growing number of tertiary graduates entering the labour market. Given the prevalence of overqualification, tertiary educated youth rather opt, in the absence of financial constraints, to remain unemployed while they keep searching for jobs that fulfil their career aspirations. It is worth recalling that with TVET, young people are more likely to acquire skills that meet labour market needs, and therefore enjoy greater employment opportunities.

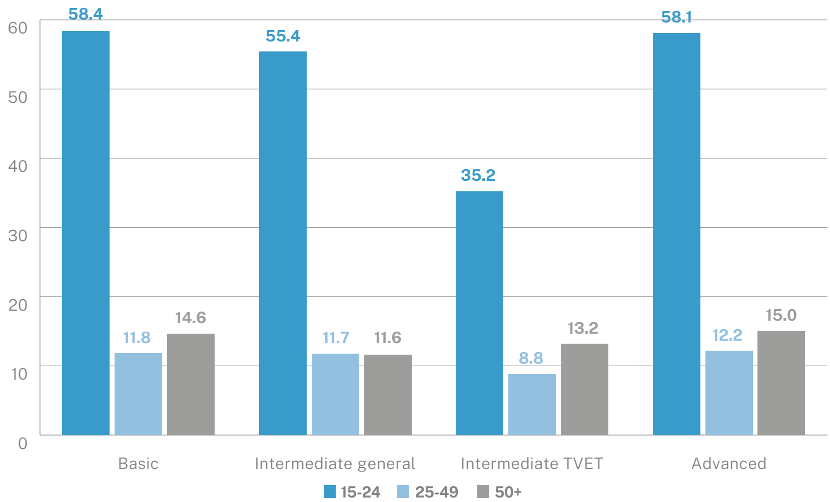
3.1.3 Inactivity rate

The third and last labour force status is captured by the inactivity rate, an indicator defined as the share of the working-age population that is economically inactive or, equivalently, out of the labour force. It is calculated as a residual since it includes all working age individuals neither employed nor unemployed. The composition of inactivity depends on the definition used for unemployment. If unemployment is defined based on the strict international statistical definition, inactivity comprises those without work, not available for work, or not seeking work. In other words, inactivity includes discouraged jobseekers who were available for work, but did not seek employment due to the lack of opportunities or inadequate skills. If the broader definition of unemployment relaxing the job search criterion is used, as it is often the case in developing countries, then discouraged jobseekers are excluded and inactivity only accounts for working age individuals neither employed nor available for work.

The distinction is important because only discouragement resulting from inadequate skills can be directly associated with qualification mismatches. Many other factors can affect the decision to look for work, including income support measures (unemployment benefits) and activation policies (to encourage unemployed workers to step up their job search), although these are rarely in place in sub-Saharan Africa where economies are largely informal.

Inactive persons unavailable for work –due to illness, disability, education, domestic duties, retirement or other reasons – are less likely to transit to unemployment or employment, at least in the short run, and their inactivity status cannot be linked to labour market conditions. Accordingly, upward inactivity trends do not necessarily reflect an increasing mismatch between labour demand and supply, but could also stem from structural changes associated, for instance, with benefit enti-

Figure 3 Inactivity rate by education level and age cohort in Kenya, 2020



Source: Own calculations based on Kenya Continuous Household Survey Programme (KCHSP) 2020

Note: Inactivity calculated as a residual after excluding employed and unemployed workers according to the strict international statistical definition of unemployment. See the Figure 1 note for the definition of aggregate levels of education.

tlement, compulsory schooling, statutory retirement age, and societal attitudes towards female employment.

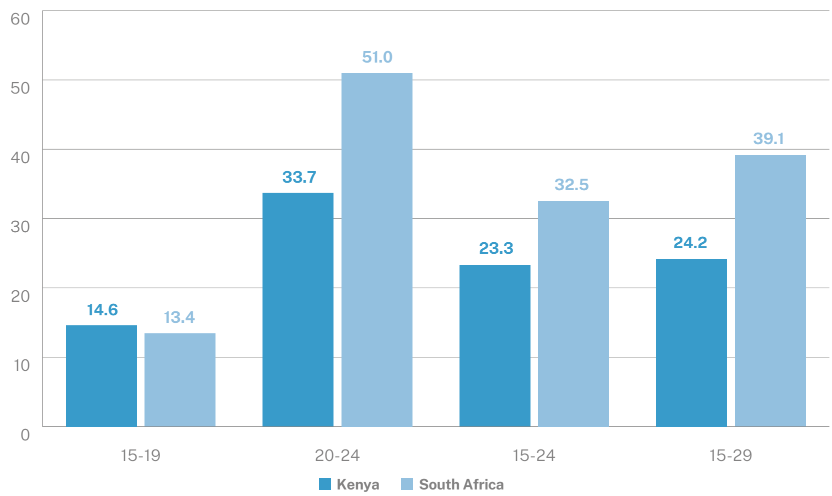
As an illustration, *Figure 3* provides the inactivity rate by education level and age cohort in Kenya for 2020. The inactivity rate is calculated as a residual after excluding employed and unemployed workers according to the strict international statistical definition of unemployment. Young people (15–24) register disproportionately high inactivity rates, which is partly explained by school enrolment. In the particular case of Kenya, the lower inactivity rate among young people with intermediate TVET education is not surprising given government initiatives to develop entrepreneurship-funding mechanisms and job placement for vocational graduates. Whatever the level of education, older cohorts are much less likely to be out of the labour force, including those aged 50+ who are over-represented in Kenya's public sector (Ministry of Labour, 2020). The latter are nonetheless more concerned by inactivity than middle-aged adults (25–49) since part of them have already retired.

3.1.4 Youth NEET rate

When focusing on the particular case of youth, it is recommended to extend the analysis of the labour force status to the share of young people not in education, employment, or training (NEET), which can be considered as a broader measure of young labour underutilization.

The youth NEET rate is one of the indicators used to track progress on the

Figure 4 Youth NEET rate by age cohort in Kenya and South Africa, latest year available



Source: Own calculations based on Kenya Continuous Household Survey Programme (KCHSP) 2020 and South Africa Labour Force Survey (LFS) 2019.

Sustainable Development Goal (SDG) 8 ‘Promote sustained, inclusive and sustainable economic growth, full and productive employment and decent work for all’ (United Nations, 2017). This indicator is defined as the percentage of young people not in education, employment, or training. The NEET rate is a broader measure than unemployment and inactivity of the untapped potential of youth who could contribute to national development through education or work. Youth NEETs are neither improving their future employability through investment in skills nor acquiring experience through employment and, therefore, bear the risk of both labour market and social exclusion. The fact that youth NEETs are not in gainful employment puts them already in a disadvantaged position. According to the latest SDG progress report (United Nations, 2022a), as many as 21.8% of young people aged 15–24 years in sub-Saharan Africa were NEETs in 2020.

To allow international comparability in line with the SDG framework, the official recommendation when calculating the youth NEET rate is to define ‘youth’ as all persons between the ages of 15 and 24 (inclusive). However, we recommend using the 15–29 age range as an alternative definition to better reflect the reality of the school-to-work transition. Indeed, the definition of ‘youth’ is usually extended to the 15–29 age range, including in sub-Saharan Africa, to account for improvements in educational attainment and, by extension, late entry into the labour market. Surprisingly, according to the African Youth Charter (AUC, 2006), Africa stands out with an upper limit set at 35 to define the youth population, which seems counterintuitive given that Africa lags far behind in terms of demographic transition. While this definition should in principle prevail when conducting analyses on sub-Saharan Africa, we do not recommend using it because the region exhibits the highest fertility rate, the lowest life expectancy at birth, and the youngest age distribution in the world (United Nations, 2022b).

As *Figure 4* shows, nearly one-fourth of youth aged 15–24 in Kenya and one-third in South Africa are not in education, employment, or training. These results are consistent with the high levels of unemployment and inactivity observed among young people. The youth NEET rate is substantially greater for young adults (20–24) as compared to teenagers (15–19) who are more likely to be attending school. Expanding the definition of youth to the age range 15–29 leads to a substantial increase of the youth NEET rate in South Africa, suggesting that older youth also struggle to find adequate employment after leaving the education system.

The particularly high youth NEET rate in South Africa raises concern. In Africa, the youth NEET rate is positively correlated with country income, southern Africa exhibiting for instance a youth NEET rate more than twice as high as in eastern Africa (ILO, 2020a). De Lannoy and Mudiriza (2019) conducted the first in-depth profiling of the youth NEET population in South Africa. They found that youth NEETs are predominantly unemployed young adults with low levels of education who are looking for work. Besides, female, black, and urban youth are found to bear a disproportionate risk of becoming NEET.

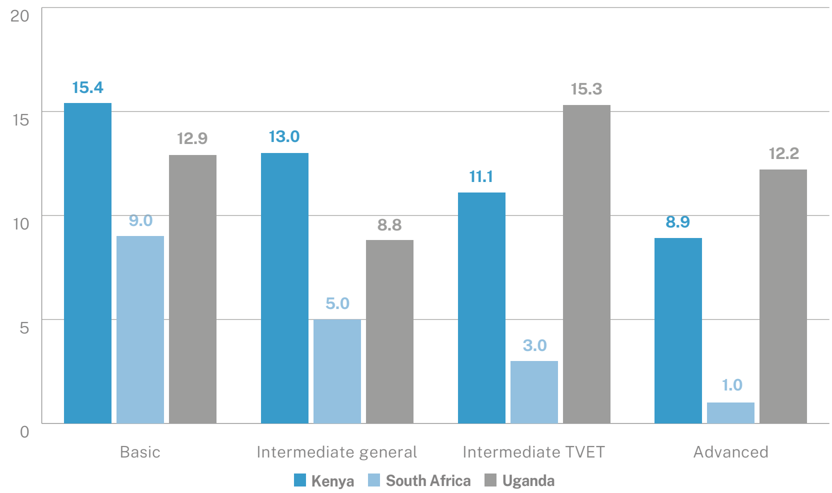
3.1.5 Time-related underemployment rate

Indicators presented so far allow for a complete depiction of the labour force status of the working-age population and provide initial insights into labour underutilization with the unemployment rate and, for the particular case of youth, the NEET rate. In this section, we go a step further in the analysis of labour underutilization by focusing on the 'visible' component of underemployment, as measured by the time-related underemployment rate. 'Invisible' underemployment is addressed in a later section on qualification mismatches, overqualification serving as a proxy measure for skills-related inadequate employment.

According to the 19th ICLS (ILO, 2013b), time-related underemployment arises when the working time of persons in employment is insufficient in relation to alternative employment situations in which they are willing and available to engage. Concretely, persons in time-related underemployment are defined as all persons in employment who, during a short reference period: (i) wanted to work additional hours, (ii) worked in all jobs less than a specified hours threshold, and (iii) were available to work additional hours given an opportunity for more work. As regards the second criterion, the 'hours threshold' is generally based on the boundary between full-time and part-time employment. To obtain the time-related underemployment rate, we divide the number of time-related underemployed workers by the total number of workers.

Since unemployment is not an option for most people in sub-Saharan Africa, time-related underemployment is the most widespread form of labour underutilization, which is linked to the high prevalence of low-productivity work (ILO, 2021). There is little evidence on the links

Figure 5 Time-related underemployment rate by education level in Kenya, South Africa, and Uganda, latest year available



Source: Own calculations based on Kenya Continuous Household Survey Programme (KCHSP) 2020, South Africa Labour Force Survey (LFS) 2019, and Uganda Labour Force Survey (LFS) 2018.

Note: See the Figure 1 note for the definition of aggregate levels of education.

between time-related underemployment and qualification mismatches. ILO (2019) shows, for instance, that underqualification among young workers in low- and middle-income countries is associated with involuntary part-time employment, among other factors.

Figure 5 provides an illustration of the time-related underemployment rate by education level in our pilot countries. Overall, South Africa is markedly less concerned by time-related underemployment than Kenya and Uganda. Different patterns emerge with the level of education. On one hand, the time-related underemployment rate steadily declines with educational attainment in Kenya and South Africa. In other words, time-related underemployment is more prevalent among low-skilled workers. For instance, in the growing South African tertiary sector, employers' preferences lean towards mid- and high-skilled workers. On the other hand, the relationship between time-related underemployment and educational attainment follows a U-shaped profile in Uganda, individuals with intermediate TVET education being the most affected (15.3%). The time-related underemployment rate is also relatively high among individuals with advanced studies (12.2%). Accordingly, better educated people in Uganda are less satisfied with their current working time and are keener to work additional hours. As time-related underemployment decreases with educational attainment, results from Kenya and South Africa tend to support the hypothesis that time-related underemployment is associated with underqualification.

3.1.6 Informal employment rate

Informal employment is, undoubtedly, the most salient and pervasive feature of labour markets in developing countries. Although it plays a key role in poverty reduction as the main source of income for the poor, informal employment is in most cases unenviable in that it encompasses jobs that generally lack basic social or legal protections or employment benefits and that may be found in both the informal and the formal sectors of the economy. Informality accounts for 70% of total employment in developing and emerging countries, sub-Saharan Africa being the most affected region with as many as 89% of informal workers; these individuals face high risks of falling into the poverty trap (OECD/ILO, 2019). Overall, informal labour markets are characterized by relative ease of entry, low labour productivity, unenforceable labour regulations, tax evasion, and inexistent social benefits (Battu and Bender, 2020), with informal businesses generating low value added and being poorly resourced (ILO, 2019).

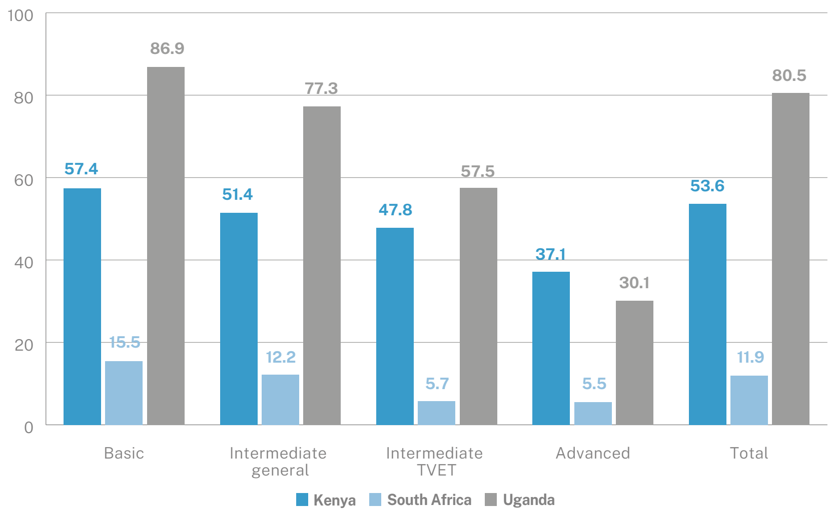
The international statistical definition of informal employment is based on the 17th International Conference of Labour Statisticians (ICLS) guidelines, whose contextual framework links the enterprise-based concept of employment in the informal sector in a coherent and consistent manner with a broader, job-based concept of informal employment (ILO, 2013a). Following the international statistical definition, we take into account all informal workers, irrespective of the type of production units they work in (formal sector enterprises, informal sectors enterprises, and households). Concretely, they are classified as informal all contributing family workers, employees not registered with a social security scheme or not entitled to paid annual leave or paid sick leave, and self-employed workers who do not keep official accounts and whose economic unit is small and not registered under national legislation.

Informal workers constitute a very heterogenous group that operates informally either by choice or out of necessity. Although some benefit from informality by avoiding taxes and regulations, it is most often associated with less rewarding, not to say subsistence, activities.

The current literature shows that informality is a strong predictor of qualification mismatch in low- and middle-income countries, whose inability of economies to generate sufficient qualified jobs fuels overqualification (see, for instance, ILO, 2019; Handel, Valerio and Sánchez Puerta, 2016; Herrera-Idárraga, López-Bazo and Motellón, 2015; Herrera-Idárraga, López-Bazo and Motellón, 2012). Overqualification can be interpreted as a resistance to unemployment (Herrera and Merceron, 2013). In order to avoid unemployment, educated people fall back on informal jobs for which they are overqualified due to the lack of skilled jobs in the formal economy. Alternatively, they can turn to foreign labour markets offering better employment prospects.

That being said, labour supply in sub-Saharan Africa and other developing regions prominently features low educational attainment. Accordingly, informality also acts as a buffer for underquali-

Figure 6 Informal employment rate by education level in Kenya, South Africa, and Uganda, latest year available



Source: Own calculations based on Kenya Continuous Household Survey Programme (KCHSP) 2020, South Africa Labour Force Survey (LFS) 2019, and Uganda Labour Force Survey (LFS) 2018.

Note: See the Figure 1 note for the definition of aggregate levels of education.

fied workers whose educational endowments fall short of the requirements for performing formal jobs. This is consistent with the relatively high rates of underqualification observed in developing countries (Battu and Bender, 2020).

As an illustration, *Figure 6* displays the informal employment rate by education level in Kenya, South Africa, and Uganda. It is evident that the incidence of informality substantially decreases with educational attainment. Workers with advanced studies are 1.5, 2.8, and 2.9 times less likely – respectively in Kenya, South Africa, and Uganda – to hold informal jobs than those with basic education. The informal employment rate exhibits a particularly sharp decline at the intermediate TVET and advanced levels in South Africa and Uganda. However, the incidence of informality among workers with intermediate TVET or advanced studies remains substantial in Kenya and Uganda.

In line with the previous discussion, results can be interpreted as follows: On one hand, the higher incidence of informal employment among less educated workers suggests that they are not qualified enough to compete for formal jobs. On the other hand, the fact that informality remains high among better educated workers suggests that they could not cope with unemployment and had to resort to less qualified jobs in the informal economy out of necessity, hence overqualification. Drawing firm conclusions requires analysing the motivation for working informally and how precisely informal employment and qualification mismatches interact. Last, it is worth recalling that formal qualifications do not capture informal skills acquired through labour market experience and training. As underqualification is partly attributable to the lack of certification among skilled workers, especially in the informal economy, recognition of prior learning can play a key role in mitigating qualification mismatches (ILO, 2019).

3.2 Qualification mismatch indicators

In this section, we turn to direct measures of qualification mismatch with indicators on qualification mismatch by level of education (vertical) and field of study (horizontal). As mentioned from the beginning, in this report we do not cover skill mismatch *per se* because of the scarcity of available data on individuals' skills and skills content of jobs in sub-Saharan Africa. We adopt, instead, a pragmatic approach by using qualifications as a proxy for skills in the absence of direct measurement. Less visible forms of mismatch relating to aspirations, career opportunities, and personality traits are also left aside because they cannot be captured by conventional indicators and require specific data sources that are rarely available in sub-Saharan Africa.

Before proceeding, a word of caution about qualifications and informal employment. ETF/CEDEFOP/ILO (2016a) warns that skills information may not be valid when it comes to informal workers. These workers tend to acquire skills through informal channels like traditional apprenticeships. As indicated earlier, the lack of certification is a key driver of under-qualification in the informal economy (ILO, 2019). Qualification mismatch indicators draw conventionally on information limited to formal education, therefore, they may not capture skills in the informal sector correctly. ETF/CEDEFOP/ILO (2016a) recommends applying non-random methods to elicit information on the informal sector's skills supply and demand,[7] or other solutions based on qualitative approaches.[8]

3.2.1 (Vertical) qualification mismatch by level of education: Normative approach

(Vertical) qualification mismatch by level of education arises when workers' level of education does not correspond to the level of education required to perform their job. When their level of education is above that required for their job, they are considered over-qualified. Conversely, if their level of education falls below that required for their job, they are considered under-qualified. The three different ways to measure vertical qualification mismatch are: the normative, empirical, and self-assessment approaches. They are all based on workers' highest level of education attained, occupation, and the correspondence between the two.

The normative approach consists in comparing the highest level of education attained by workers based on the International Standard Classification of Education (ISCED) (UNESCO-UIS, 2012) and their occupational skill level, defined as a function of the complexity and range of tasks and duties to be performed in an occupation, based on the International Standard Classification of Occupations (ISCO) (ILO, 2012). Concretely, we classify occupations into several broad groups according to the occupational skill level and assign to each broad group the corresponding level of education required. Individuals working in a given broad occupational group and having the

7 For example, a non-random establishment survey can be conducted in particular areas where local experts have identified a major informal sector activity (e.g., markets or specific streets in urban areas) (ILO, 2013a).

8 Expert consultations, interviews, and focus groups with businesses and workers.

assigned level of education are considered well-matched. Those having a higher (lower) level of education are considered over(under)-qualified.

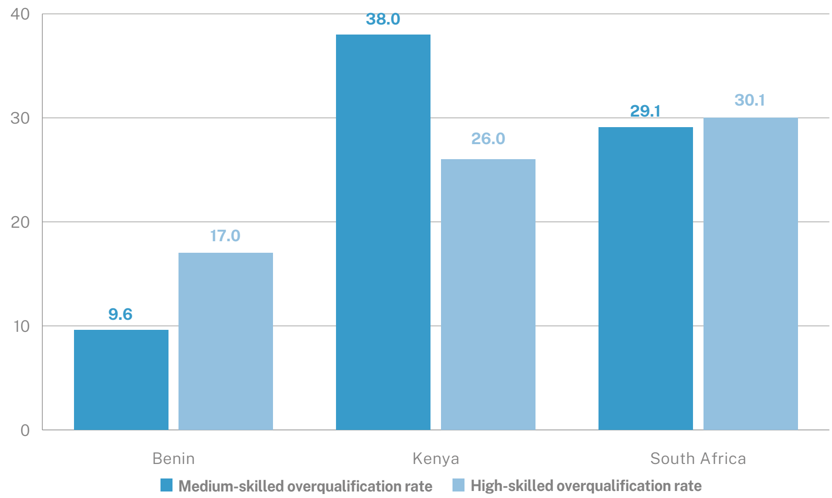
The empirical approach, which will be the focus of the next section, differs in that it uses the modal level of education – or alternatively the modal, median, or mean years of schooling – of all workers in a given occupational group as a proxy for the required level of education in that occupational group. In turn, the self-assessment approach relies on the required level of education as perceived and reported directly by workers to perform their job.

ILO (2018a) explains in detail the strengths and weaknesses of the three approaches and concludes that, considering the limitations of the empirical approach and the subjectivity of the self-assessment approach, preference should be given to the normative approach. While easy to implement, the empirical approach does not capture well current educational requirements and lacks stability since the modal level of education is affected by the presence of older and more experienced workers, and changes over time with the evolution of workers' educational profile. In addition, it assumes that all jobs within each occupational group have the same educational requirements, which is questionable. By contrast, the self-assessment approach takes into account the heterogeneity of jobs in terms of (self-perceived) educational requirements but the resulting subjectivity bias leads to interpretation issues that, in our opinion, make this approach not suitable for the analysis of qualification mismatch. For instance, OECD (2017) shows that the proportion of underqualified young workers in developing countries is largely underestimated when the self-assessment approach is used as compared to the normative approach, indicating that individuals tend to overrate the actual relevance of their qualifications.

Despite being considered the most reliable, the normative approach is not exempt from certain limitations too. First, the normative approach also relies on the homogeneity assumption according to which all jobs within each occupational group have the same educational requirements, which is unlikely to hold true in practice. Second, national assessments of jobs' educational requirements, which are difficult to develop, are typically lacking or outdated in sub-Saharan Africa. Therefore, the analysis of vertical qualification mismatch has to draw on the general ISCO framework with educational requirements defined by the skill levels associated with major occupational groups. In other words, the analysis is based on the most aggregate level (1-digit code) of the ISCO classification, which tends to overestimate the extent of vertical qualification mismatch (ILO, 2018a). Ideally, the measurement of vertical qualification mismatch should be based on educational requirements as specified in relevant legislation or national practice for more specific and homogeneous occupational groups. Given these limitations, we recommend using in addition the empirical approach, which we describe in the next section, as an alternative measurement of vertical qualification mismatch.

With vertical qualification mismatch, we are particularly interested in evidencing labour underutilization, overqualification serving as a proxy measure for skills-re-

Figure 7 Vertical qualification mismatch (normative approach) in Benin, Kenya, and South Africa, latest year available



Source: Own calculations based on Benin Integrated Regional Survey on Employment and the Informal Sector (ERI-ESI) 2018, Kenya Continuous Household Survey Programme (KCHSP) 2020, and South Africa Labour Force Survey (LFS) 2019.

lated inadequate employment, which constitutes one major form of 'invisible' underemployment as already seen. We recommend computing the following indicators on overqualification, accounting only for workers who already left school:

- **Medium-skilled overqualification rate**: share of medium-skilled workers, that is, with an upper (general or vocational) secondary education, holding low-skilled jobs, that is, elementary occupations (ISCO major group 9). Elementary occupations only require primary education (ISCED level 1).

- **High-skilled overqualification rate**: share of high-skilled workers, that is, with a tertiary education, holding low- or medium-skilled jobs, that is, clerical support workers (ISCO major group 4); services and sales workers (ISCO major group 5); skilled agricultural, forestry and fishery workers (ISCO major group 6); craft and related trades workers (ISCO major group 7); plant and machine operators and assemblers (ISCO major group 8); elementary occupations (ISCO major group 9).

Figure 7 displays the medium- and high-skilled overqualification rates in Benin, Kenya, and South Africa. In Benin, 9.6% of medium-skilled workers with an upper secondary education hold elementary occupations (medium-skilled overqualification rate), and 17.0% of high-skilled workers with a tertiary education hold low- or medium-skilled occupations (high-skilled overqualification rate). The rates rise, respectively, to 38.0% and 26.0% in Kenya, and 29.1% and 30.1% in South Africa. Although Benin fares better than other countries, the incidence of overqualification, especially among high-skilled workers, remains fairly high. With the noticeable exception of Kenya, high-skilled workers appear to be more concerned by overqualification than medium-skilled workers. These results are consistent with the literature which shows that Africa stands out as the region with the largest share of tertiary educated youth engaged in medium- or low-skilled jobs (OECD, 2017). This is because high-skilled job creation does not keep pace with the growing number of tertiary graduates entering the labour market. Overqualification is consistently found to be associated with decent work gaps, including lower earnings and job dissatisfaction (ILO, 2019; OECD, 2017; Quintini, 2011).

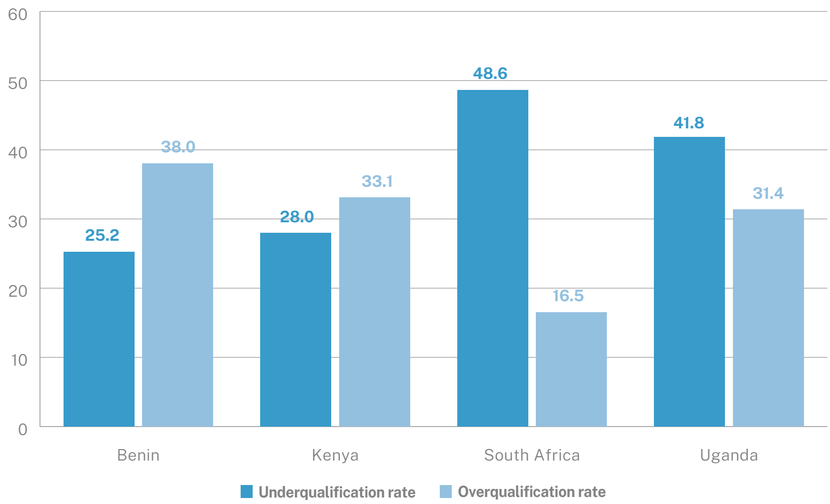
3.2.2 (Vertical) qualification mismatch by level of education: Empirical approach

We deviate from the 20th ICLS guidelines (ILO, 2018a) in recommending using both the normative and the empirical approaches to measure vertical qualification mismatch. As already discussed, the normative approach requires an elaborate normative setting for identifying educational requirements. In practice, sub-Saharan African countries tend to rely on the general ISCO framework, which is unlikely to fully reflect national contexts. For this reason, it is recommended to use the empirical approach as an alternative measure of vertical qualification mismatch.

With the empirical approach, we proxy educational requirements by the most frequent (modal) level of education of workers in each occupational group. Note that other methods to empirically determine the educational requirements of occupations exist, but they are less reliable. For instance, an older stream of literature uses a confidence interval of one-standard deviation above or below the average (mean, median or modal) number of years of schooling to identify, respectively, over- and under-qualified workers in each occupational group (see, for example, Bauer, 2002). The problem with this method lies in the lack of consensus on how to convert levels of education into years of schooling (ILO, 2018a). Another method consists in using the modal value of the self-assessed level of education required to perform the job according to workers in each occupational group. However, this method bears a subjectivity bias that makes it not suitable for a sound analysis of vertical qualification mismatch. The most appropriate way to proceed is then to rely on the modal level of education in each occupational group, workers being classified as over-qualified if their level of education exceeds that threshold, or over-qualified if it falls below.

As mentioned earlier, one of the limitations of the empirical method relates to the lack of stability of the modal level of education of workers in each occupational group, which becomes particularly acute when small samples are used. Vertical qualification mismatch can be hard to interpret when the modal level of education changes over time with the evolution of workers' educational profile. Interpretation issues also arise when the modal level of education in each occupational group is affected by the age distribution of workers. Indeed, older workers tend to have more experience than younger ones but also lower qualification levels. In the absence of a proper normative setting, the empirical method allows for a simple identification of educational

Figure 8 Vertical qualification mismatch (empirical approach) in Benin, Kenya, South Africa, and Uganda, latest year available



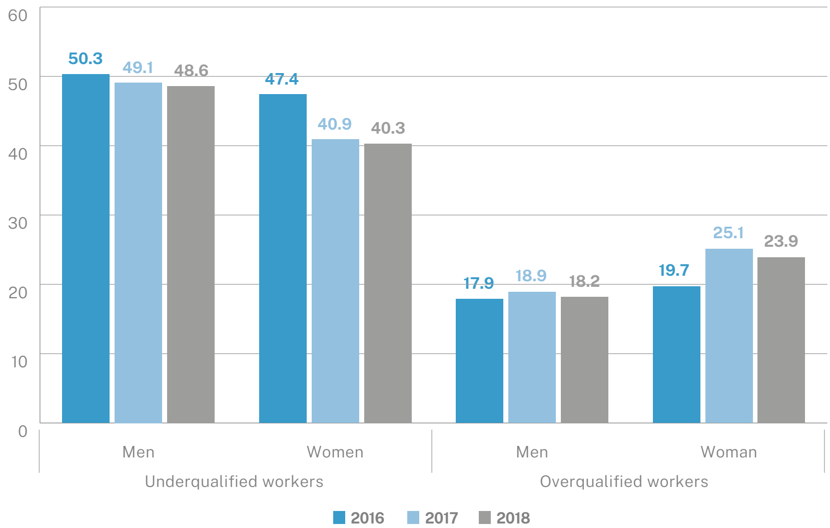
Source: Own calculations based on Benin Integrated Regional Survey on Employment and the Informal Sector (ERI-ESI) 2018, Kenya Continuous Household Survey Programme (KCHSP) 2020, South Africa Labour Force Survey (LFS) 2019, and Uganda Labour Force Survey (LFS) 2018.

requirements by determining the modal level of education of workers in each occupational group over time. It is widely used and recommended as an alternative to the normative approach for the measurement of vertical qualification mismatch (ILO, 2018a).

Figure 8 provides a comparative illustration of vertical qualification mismatch in our four pilot countries based on the empirical approach. In contrast with the normative approach, we compute the overqualification rate accounting for all workers regardless of their level of education, and extend the analysis of vertical qualification mismatch to underqualification. In South Africa and Uganda, the number of underqualified workers reaches disproportionate levels, thus pointing to a serious shortage of skilled workers. In turn, Benin and Kenya are more concerned by overqualification, suggesting that the deficit of skilled jobs in these countries is particularly acute. Strikingly, the higher prevalence of overqualification in Benin is at odds with previous results based on the normative approach, which showed that Benin fares better in this respect compared to Kenya and South Africa. This finding illustrates well how sensitive the measurement of vertical qualification mismatch can be to the approach used.

To deal with population heterogeneity, vertical qualification mismatch can be disaggregated for different sub-groups based on characteristics like age, sex, education, occupation, and sector of activity. For instance, *Figure 9* breaks down vertical qualification mismatch, measured using the empirical approach, by sex in South Africa for the period

Figure 9 Vertical qualification mismatch (empirical approach) by sex in South Africa, 2016–2018



Source: Own calculations based on South Africa Labour Force Survey (LFS).

2016–2018. Trends analysis allows a better understanding of the empirical approach stability and the evolution of vertical qualification mismatch over time. The figure reveals a clear downward trend for underqualification, especially among women, but not for overqualification. On the contrary, overqualification appears to gain ground among women whereas it remains fairly stable for men. These findings likely reflect the fact that women are catching up in terms of educational attainment and, therefore, compete more and more for qualified jobs. Further disaggregation by age, education, and other factors would help in refining the profile of under- and over-qualified workers. The economic conjuncture should not be overlooked either as it has been shown, for instance, that overqualification tends to rise in the aftermath of a recession due to the resulting paucity of available jobs (Quintini, 2011).

3.2.3 (Horizontal) qualification mismatch by field of study

Qualification mismatch can also relate to the field of study, in which case it is deemed horizontal. This form of qualification mismatch arises when workers' occupation does not correspond to the main field of study of their highest level of education. Horizontal qualification mismatch can also be measured following the normative, empirical, and self-assessment approaches. As for vertical qualification mismatch, it is recommended to give preference to the normative approach when measuring field-of-study mismatch for the same reasons as stated before (ILO, 2018a).

To measure horizontal qualification mismatch following the normative approach, we compare workers' occupation and field of study based, again, on the ISCED and ISCO classifications. If workers' field of study does not correspond to the requirements for their occupation, then they are considered horizontally mismatched. The normative approach thus requires establishing a clear correspondence between fields of study and occupations, which represents a complex task. Wolbers' (2003) seminal paper provides a table of correspondence between occupational groups from the ISCO-88 classification at the three-digit level and fields of study from the ISCED-F 1997 classification. Updated correspondences between occupational groups and fields of study based on ISCO-08 three-digit and ISCED 2011 classifications can be found in Montt (2017) and OECD (2014).

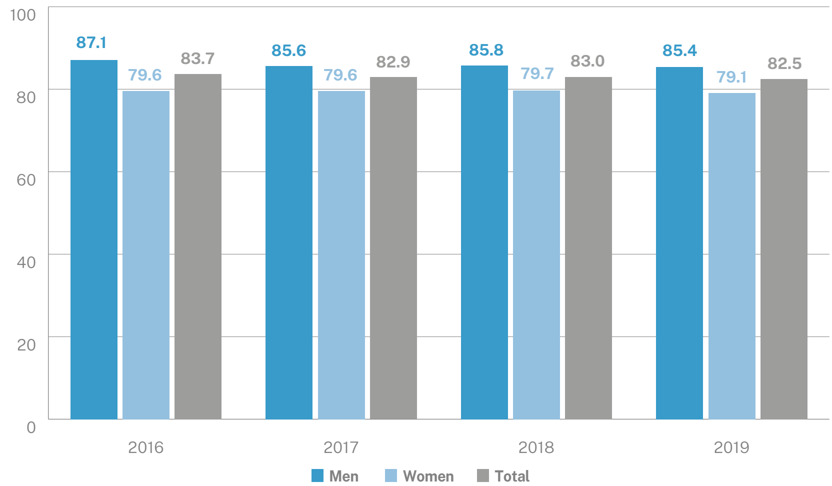
The normative approach is not exempt from certain limitations. Only educated workers with a specialised field of study can be accounted for, which is particularly problematic in sub-Saharan Africa, where a minority of students attain secondary TVET or tertiary education, meaning that the majority of workers entering the labour market lack any specialisation. As a consequence, the number of observations in household surveys tends to be small, which affects the stability and reliability of the field-of-study mismatch indicator and resulting analyses. As for vertical qualification mismatch, skills informally acquired are not captured while they can be equally relevant to the occupation, if not more, than formal education specialisation. The analysis of horizontal qualification mismatch is also constrained by the lack of data. In contrast with the level of education, information on the field of study is not systematically available in household surveys conducted in sub-Saharan Africa.

The empirical evidence on field-of-study mismatch is less prolific compared to vertical qualification mismatch and focusses typically on developed countries (ILO, 2019). Beyond data gaps and measurement issues, this probably owes to the fact that the factors associated with field-of-study mismatch are less straightforward. However, some studies converge in that field-of-study mismatch carries a significant wage penalty only when workers are overqualified (see, for instance, Montt, 2017 and 2015). The latter is explained in particular by field saturation: workers who cannot find work in their field of study may have to accept jobs that are below their qualification level in other fields. When associated with overqualification, field-of-study mismatch reduces the level of job satisfaction and increases the risk of unemployment, in addition to the wage penalty (Montt, 2015).

Accordingly, field-of-study mismatch *per se* does not necessarily reflect a negative outcome. For instance, older workers are more concerned by field-of-study mismatch, because their experience outweighs their formal education when it comes to career decisions (Montt, 2017). In addition, more experienced workers face a lower wage penalty resulting from field-of-study mismatch, indicating that education and work experience are somehow substitutable (Nordin et al., 2010).

As an illustration, *Figure 10* presents the share of field-of-study mismatched workers in South Africa separately for men and women for the period 2016–2019. Clearly, the vast majority of workers, men

Figure 10 Share of field-of-study mismatched workers in South Africa, 2016–2019



Source: Own calculations based on South Africa Labour Force Survey (LFS).

more than women, hold jobs that are unrelated to their field of study. As field saturation most certainly comes into play, this finding calls, in particular, for enhancing skills needs assessment and anticipation as well as career guidance to help individuals make informed choices about their career path and subsequently prevent qualification mismatches. However, the observed overly high number of field-of-study mismatched workers casts doubts on data accuracy, which further calls for better tackling measurement issues. Ideally, more detailed and country-specific tables of correspondence between fields of study and occupations would be needed to avoid overestimating horizontal qualification mismatch.

Over the period, the share of field-of-study mismatched workers follows a slightly decreasing trend. Data stability matters because, in the absence of external shocks, large year-to-year changes are implausible in the labour market. Further investigation can be conducted to understand the reasons for gender disparities in field-of-study mismatch, which could be linked, for instance, to differences in educational or occupational choices.

All in all, we recommend the computation of the counts and rates of vertically and horizontally mismatched workers for different sub-groups in order to identify those most at risk. Indicators should be disaggregated to the extent possible – i.e., provided that reliable and stable results can be obtained – by age, sex, level of education, occupation, sector of activity, as well as area of residence to account for spatial disparities.

Chapter 4
Preventing qualification mismatch: Skills needs assessment and anticipation

Now that we are familiar with the concepts surrounding qualification mismatches and the most relevant indicators to analyse them, we consider skills needs assessment and anticipation, which make up an integral part of an effective policy response to prevent skill imbalances.

According to OECD (2016), policy intervention can help successfully address skill mismatches only if there is comprehensive information on current and future skill needs. Skill anticipation provides the means to identify future imbalances, thus allowing individuals and firms to take informed decisions. In particular, skill anticipation helps reduce the likelihood of any given occupation or sector of activity becoming highly saturated in the future (Montt, 2017). Skill needs information can notably serve: (i) in labour market policy, to update occupational standards and design or revise apprenticeship, retraining, and on-the-job training programmes; and (ii) in education policy, to develop qualifications, curricula, and career guidance (ILO, 2017; OECD, 2016).

In sub-Saharan Africa, skills gaps and shortages are persisting, thus prompting heightened efforts towards more comprehensive demand-led skills development strategies. In this context, assessing the current and future prospects on the labour market proves to be key for addressing the imbalances between the demand for and supply of skills.

Accordingly, this chapter goes beyond the analysis of qualification mismatch by providing a general description of existing methods to assess and anticipate skills needs, which can be classified into: (i) quantitative, (ii) qualitative, or (iii) mixed methods. The best practices consist in either skills foresighting exercises or the use of quantitative skills forecasting, if necessary simplified in terms of underlying macroeconomic models, assumptions or data requirements. Skills anticipation exercises are, however, rare in the sub-Saharan African context as they require stable data inputs along with modelling and analytical experience.

Sectoral studies are presented as an illustration of mixed methods combining quantitative and qualitative information. ILO's Skills for Trade and Economic Diversification (STED) sectoral studies, which have already been successfully implemented in some African countries, provide – among others – a thorough analysis of the economic context and the skills and training aspects of a complete sector in a country.

Finally, the chapter discusses the use of big data approaches to identify emerging occupations and skills. All the methods presented in this chapter require a significant amount of qualitative or quantitative inputs along with analytical capacity.

4.1 Quantitative methods: Skills forecasting

This section describes the two most commonly applied quantitative methods to anticipate skills needs: (i) skills forecasting models, and (ii) Input-Output (IO) tables and Social Accounting Matrices (SAM).

4.1.1 Skills forecasting models

Analysing the future supply and demand for skills is usually done with quantitative skill forecasts.[9] Rather than providing detailed information on skills, skills forecasting draws on sectoral employment detailed out into occupations and qualifications. Typical representations are thus supply and demand imbalances identified at the two-digit ISCO classification level, along with a similar breakdown in qualification levels and fields. As a rule of thumb, the information will not be more detailed than the available information in comparable time series data on the labour market from several waves of labour force surveys.

The method consists in developing an occupational forecasting model that quantifies and projects skills demand by sector and occupation as well as skills supply by qualification to identify future skills imbalances. It usually involves multi-module modelling that includes a macroeconomic (general equilibrium) model providing medium-term forecasts of employment by sector, modules identifying the occupational development in sectors, supply-side modules by qualification, and sometimes elements of replacement demand. These types of set-ups are used in many countries throughout the world, each with slight adaptions given the data situation, the main or initial goal of the forecasting model, and the development over time.[10]

The occupational forecasting model relies on adequate labour market data, both in quality and in the data series length. It can also be complemented by procedures or assumptions based on a qualitative methodology.

The inputs necessary for forecasting skills demand by occupation are (ILO, 2015):

- estimates of the future level of aggregate GDP or output;
- estimates of future employment by industry, usually derived from the macroeconomic module;
- occupational distribution by sector (historic time series);
- estimates of replacement demand (based on age distribution within occupations).

Sometimes the inputs listed above are set by assumption and derived from underlying data within the forecasting framework (ETF/CEDEFOP/ILO, 2016b).

9 See ETF/CEDEFOP/ILO (2016b) for a detailed description of skills forecasting.

10 See ETF/CEDEFOP/ILO (2016b) for a summary of implementation guidelines for these methods.

Skills supply by occupation is derived from these models, based on underlying distributions of the data. Often, time series over several years are needed to estimate the likely future developments. Inputs include:

- population by age, sex and education, based on historical time series and population forecasts;
- estimates of the labour force participation by education, based on historical time series;
- estimates of (future) graduates by age, sex, and education.

Skills forecasting models vary according to: (i) their coverage (e.g., national, regional, or by sector/occupation); (ii) their frequency and period; and (iii) the type of modelling approach and related data requirements.

Because of their complexity, these exercises tend to be carried out predominantly in high-income countries (ETF/CEDEFOP/ILO (2016b). The availability of quantitative forecasting models and related techniques may be a challenge for emerging and developing economies. However, they can be simplified and combined with qualitative information to make their implementation possible.

In the context of sub-Saharan Africa, several elements should be considered. First, time-series data on employment by sector, occupation, and qualification are key for the forecasting model, but they generally lack in the region. When time-series data exist, they often contain a limited number of observations, leading to fluctuations when combining occupations and qualifications, and extrapolating their evolution over time with the forecasting model. Second, the availability of macroeconomic models that provide mid-term forecast (5–10 years) for the national economy and allow the translation into employment by (detailed) economic sector are also rare. These two elements are at the heart of a quantitative demand forecast. Similarly, supply forecast would require stable time -series data on qualifications for the past years, preferably at a detailed level.

Skill mismatches in quantitative forecasts are determined by combining qualifications with occupations in the forecasting period. They identify the unfulfilled demand at the occupational level and the resulting qualifications needs. However, this can only be done at a level of granularity that ensures stable historical series with the underlying data. By and large, given the prevailing data gaps in sub-Saharan Africa, it is recommended to first concentrate on data collection and the analysis of current skill mismatches before turning to a quantitative model to anticipate skill needs.

4.1.2 Input-Output Tables and Social Accounting Matrices

In low- and middle-income countries, sometimes simplified approaches are used. These approaches use the Input-Output (IO) Tables and Social Accounting Matrices (SAM). The latter are consistent data frameworks that capture the information contained in the national income and product accounts, a Supply-Use Table (SUT), and the monetary flows between institutions. They can provide useful information to assess and anticipate skills mismatch. They link traditional

Table 1 Example of Input-Output Table

Billions of Euros

		Products						Final use					Total output at basic prices
								Final consumption					
		Agriculture	Manufacturing	Construction	Trade, trans. and comm.	Finance and business service	Other services	Households	Government	Gross fixed capital formation	Changes in inventories	Exports	
Products		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Agriculture	(1)	3	20				1	9			3	5	42
Manufacturing	(2)	7	394	48	56	11	30	250	7	95	-58	611	1451
Construction	(3)	1	11	18	8	28	10	5		153		1	234
Trade, trans. and comm.	(4)	4	139	17	181	38	40	317	15	39	6	111	907
Finance and business service	(5)	6	131	30	124	261	51	313	3	25		66	1010
Other services	(6)		18	3	12	17	47	147	472	2		2	721
Total at basic prices	(7)	21	713	116	382	355	179	1041	497	314	-49	795	4365
Imports	(8)	5	283	17	58	31	21	128	9	61	31	189	833
Taxes less subsidies on products	(9)	2	10	2	12	17	24	151	6	34			257
Total at purchasers' prices	(10)	27	1007	135	452	402	224	1319	513	409	-18	984	5455
Compensation of employees	(11)	6	308	69	294	191	364						1232
Other taxes less subsidies on production	(12)	-6	-2		-1	5	-7						-12
Consumption on fixed capital	(13)	8	79	5	60	160	63						375
Net operating surplus / Net mixed income	(14)	7	60	25	101	252	77						523
GVA	(15)	15	445	99	454	608	497						2117
Total input at basic prices	(16)	42	1451	234	907	1010	721	1319	513	409	-18	984	

Source: Table extracted from United Nations (2018).

macro-economic indicators such as the Gross Domestic Product (GDP) to other socio-economic indicators (e.g. population and income distribution), divide households into meaningful sub-groups (e.g. occupational groups and skill levels), and highlight the economic significance of each of them. They avoid detailed macroeconomic modelling, which is the most technical aspect of skills forecasting.

SAM and IO Tables are used for modelling impacts of changes in final demand for products on the production of different sectors and employment. They allow demonstrating how a change induced by a shock on the demand side will influence the structure and volume of employment and skills demand.

SAM and IO Tables are simpler models used in developing countries to compensate for data unavailability or poor quality (ETF/CEDEFOP/ILO (2016b). They are not designed to make economic forecasts, but rather to model changes in final demand through the linkage of interim products of different sectors and their consequences for employment. The core of the model is an IO Table showing how much each sector produces, how much of this production is used by other sectors, and the final demand for each sector's production. Final demand is usually distinguished by households, government, export, and for capital creation and inventories. The model can translate the final demand for products of a specific sector into inputs from other sectors which support it. *Table 1* below provides an example of an IO Table taken from United Nations (2018).

The following core data requirements are sufficiently low to be applicable in different country contexts:

a) IO Table for the last available year;
b) data on the volume and the structure of employment (typically from a labour force survey or eventually from an establishment survey).

IO Tables are often used when complex macroeconomic models do not exist. They are simpler and require only inputs that are often available at the national level. They are relatively flexible and applicable in both developing and developed countries. United Nations (2018) provides detailed modelling applications of IO Tables.

Like other models, IO Tables are built on strong assumptions that depict an oversimplified representation of the economy, therefore, modelled impacts should be taken with caution and considered as gross approximations. According to (ETF/CEDEFOP/ILO (2016b), basic IO Tables assume that:

- Prices are fixed and do not change with changing demand (in practice, prices tend to increase with demand).
- Productive relationships remain stable (in practice, change in technology, for example, may require inputs from different sectors in the future).
- There are no constraints on the supply side (in practice, skill mismatch can cause a significant supply side constraint).
- Everything is happening at the same time; the changes in demand influence the inputs and employment in the same period (in practice, the effect of changes tends to be sequential).

More advanced IO Tables can be developed, depending on data availability, to eliminate some assumptions. Using SAM instead of IO Tables allows distinguishing between different types of households or analysing the impact of taxes and government spending in more detail. The time dimension can be integrated by using dynamic variants of IO and SAM models.

4.2 Qualitative methods: Skills foresighting

Skills foresighting is a methodology used to anticipate skill needs, which requires less formalized data and depends on the social dialogue with key experts and stakeholders thinking collaboratively about future scenarios. It aims to set skills priorities, mobilize action to shape the future, and pursue identified scenarios (ILO, 2015; Cedefop, 2021a). While not compulsory, using quantitative information (labour market information and quantitative forecasts) is recommended, in which case the foresight literature refers to 'mixed-methods' combining quantitative and qualitative information.

Skills foresighting can be exploratory or normative (ETF/CEDEFOP/ILO (2016b). Explorative approaches aim at understanding, by looking at present data, what could have happened if an event had happened. They usually rely on expert panels, Delphi methods, horizon scanning, scenarios, and cross-impact analysis. Instead, normative methods first define goals that should be achieved or are desirable and derive policies for the present. Normative methods include backcasting, morphological analysis, relevance trees, and road mapping. Scenario developments are instruments similar to skills foresighting but only prepare for potential future challenges, not predictions.

Foresight sessions require skilful moderators. They also require expertise in engaging all stakeholders and in compiling diverse qualitative information into a report. The advantages of these methods are that they directly involve their users, who may be able to address problems in greater depth, allowing for exchanging views and considering uncertainties for the future. The disadvantages are that they may be non-systematic, inconsistent, or subjective.[11] *Box 1* below provides an example of a foresight model derived from the national industrial apprenticeship service, referred to as SENAI, in Brazil.

Foresights in the context of skills anticipation can be useful instruments in bringing anticipatory elements into the analysis of skills, skills mismatch, and other potential labour market imbalances. They are less dependent on detailed and regular data updates as it is the case with quantitative skills forecasting. Yet, if done well, they can uncover key areas in which mismatches might occur and provide solutions to overcome them.

An important element of any foresight exercise is collecting and analysing background information, including quantitative information on the current and, if projections are available, future developments in areas related to the labour market (e.g., population, education, employment, and economic development).

A foresight exercise should be well-planned and done under the guidance of an experienced foresight specialist, at least if an initial set-up of the methodology is required. Just as in quantitative forecasting, foresighting requires the correct use of its instruments and the correct interpretation of the results (ETF/CEDEFOP/ILO (2016b).

11 For a detailed description and implementation guidelines on skills foresighting, see (ETF/CEDEFOP/ILO (2016b) and, in the context of technological change, Cedefop (2021).

Box 1. Example of foresight model: The SENAI programme

SENAI (*Serviço Nactional de Aprendizagem*, or the National Industrial Apprenticeship Service) is a network of not-for-profit secondary level professional schools established and maintained by the Brazilian Confederation of Industry. The SENAI's foresight model, which is a sectoral model designed for the industrial sector, was initiated in 2001 in Brazil and replicated in different countries as a good model for skills anticipation. One of the success factors of the model is that the private sector takes a lead role in skills forecasting and in the provision of training itself, thereby ensuring skills supply and skills demand matching.

Stakeholders are organized and divided into different groups to take specific responsibilities. The application of the model requires the involvement of different working groups, including the executive groups (EG), the Delphi and Expert Panels (DEP), and Sectoral Experts (SE). Each group applies its expertise and is responsible for different practices.

The foresight model captures industrial, technological, and organizational changes and their impacts on future employment. Specifically, technological foresight aims to prospect emerging technologies of the specific sectors within 5–15 years and analyse their impacts on jobs. Three main foresight methods are applied, including brainstorming (with university and school experts), workshops, and DEP discussions to produce a technology emerging list, considering the possible diffusion and impacts on the labour market. Organizational foresight studies new forms and tendencies of the employer´s organization within the sector. This step may also include DEP with sectoral specialists from universities, government, vocational education schools, and the owner industry. Besides, information on sector performances and trends is also collected to create the background for the analysis.

The results from technological and organizational foresight and sectoral information analysis are gathered to undertake an occupational impact analysis. This practice aims to identify and evaluate the probable professional changes introducing emerging technologies and organizational changes.

Next, the model integrates activities focusing on two main questions: (i) How many workers by occupation and industrial sector will be demanded soon? (ii) What changes to the professional profile will be required in terms of knowledge, skills, and abilities? Various quantitative and qualitative methods and approaches are combined and implemented to produce information, which the executive group will discuss in the thematic workshops. Finally, recommendations are provided to guide the development of future activities in the areas of vocational education, technological services, and the updating of human resources.

Sources: OECD/ILO/World Bank (2016) and ILO/Cinterfor and SENAI (2013).

The key steps for implementation of a foresight programme can be described as follows:

a) **Define the foresight area**: it is important to identify the core issue of the foresight exercise. The more precise the definition is, the more detailed the outcomes will be, especially if choices are taken to ensure this in the subsequent steps. For example, while foresight could be considered to identify future skill needs in a country, a narrowing of this 'core issue' onto the skill needs in a specific sector or the skill needs for graduates of TVET schools in a specific region will lead to more concrete outcomes. It would allow concentrating on data, experts, and stakeholders that are informative for the specific issue addressed.
b) **Define the purpose of the foresight exercise**: a precise purpose of the foresight exercise will, on the one hand, help identify the stakeholders and experts to be involved in the process, and, on the other hand, ensure that the foresight exercise will provide the answers we look for. Foresights can identify qualitative directions, problems, and issues. However, it is not well suited to precisely quantify the size of a problem, the future demand, or the number of graduates needed. By defining a suitable purpose and bringing on board the relevant stakeholders, the foresight exercise allows identifying key issues in a collaborative way, understanding the different views from stakeholders, and sharing a common understanding of their respective roles. In short, the process of foresight uncovers key information and a common understanding of problems.
c) **Include background information and contextual factors**: to develop a well-grounded foresight, background and contextual information should be collected, shared, and considered when developing potential future outcomes. In the context of skills needs anticipation, key labour market information on labour demand and supply, along with current skill mismatches, should be researched, analysed, and shared with all stakeholders. A common understanding of the current situation should provide the foundation on which future issues can be discussed. Of course, key constraints at the country level should be considered. These include the economy, the education system, the institutions concerned by the expected changes drawn from the foresight exercise, and the likelihood or speed of their implementation.
d) **Clearly define the foresight programme**: first, define the scope and target audience of the foresight. Second, outline the process through which stakeholders and experts participating are informed and take part in the exercise. And third, inform participants about their role in the process and the expectations related to their participation. It should also be transparent on steps (e.g., multiple meetings, review of interim outcomes) taken and when they should be concluded.
e) **Develop and use key results**: the results of a foresight exercise can be manifold and depend on the core issue addressed. In general, results provide qualitative insights into an issue that experts and stakeholders discuss to identify the challenges and potential future developments. They often analyse critical issues that could overcome future problems and provide

policy recommendations based on the outcomes. Key stakeholders are involved in identifying challenges and developing a common understanding of each other's constraints and opportunities. Therefore, the expected outcome is for key stakeholders to reach a consensus on policy recommendations.

4.3 Mixed methods combining quantitative and qualitative information: The case of sectoral studies

Skills needs assessment and anticipation are often carried out from a sectoral angle rather than at the national or regional level. Several aspects can be more easily identified within a sector: the number of occupations and qualifications relevant to a sector is lower than in the labour market overall. Few actors are involved, allowing for easier stakeholder participation and deeper qualitative analysis of the sector's occupations, skills, and qualifications. Furthermore, by identifying strong or emerging sectors, a learning experience likely to provide replicable results can be generated.

Usually, sectoral studies use a combination of quantitative and qualitative tools as it is the case, for instance, in the Skills for Trade and Economic Diversification (STED) programme. These studies are strong on sectoral specifics but remain partial and can be inconsistent across sectors (Wilson, Woolard and Lee, 2004).

The methodology developed and implemented by the ILO as part of the STED programme provides a comprehensive example of a sectoral approach based on mixed methods combining quantitative and qualitative information (see Box 2 below for some insights into the STED project conducted in Malawi). Gregg, Jansen, and von Uexkull (2012) developed a practical guide on the STED methodology, which is designed to provide an outlook of existing and future skills shortages based on the anticipation of sector development and growth opportunities, and the analysis of current skills supply and demand. Specifically, the STED methodology allows anticipating the type of skills needed, the number of workers who will be required by skill type and the gap between future skill requirements and current skills supply, in both quantitative and qualitative terms. Practical solutions can be derived on how existing training and education institutions can help to better respond to skills demand, among other aspects.

Box 2. An example of sectoral studies using mixed methods: ILO's Skills for Trade and Economic Diversification (STED) project in Malawi

The STED methodology was applied in Malawi in two sectors prioritised by stakeholders, namely oilseeds and horticulture, based on desk research and three surveys: (i) the Oilseeds Enterprise Survey (OES), (ii) the Horticulture Enterprise Survey (HES), and (iii) the Skill Supply Mapping and Analysis Survey (SSMAS), which provides insights on skills provision in training institutions. Both sectors are largely underdeveloped with almost all firms serving the domestic market.

The oilseeds and horticulture sectors are confronted with significant skills shortages, both in terms of the number of workers and quality of skills. In the oilseeds sector, firms find it difficult to recruit engineers, scientists, technicians, operatives, packaging workers, managers, and administrators. In the horticulture sector, firms find it difficult to recruit managers, technicians, operatives and workers in packaging, logistics, transportation, marketing, customer service, sales, and administration. In addition, the majority of firms in both sectors consider that newly recruited university and vocational school graduates lack the required knowledge and skills.

To address skills needs, the study recommends for the oilseeds sector to: (i) design tailor-made short-term skills upgrading programmes, (ii) design enterprise-based training for existing workers, (iii) introduce an apprenticeship programme, and (iv) strengthen the capacity of higher learning institutions. For the horticulture sector, the study recommends to: (i) develop tailor-made Work-Integrated Learning (WIL) programmes which meet industry competency needs; (ii) develop productivity, disease, and pest control training programmes for small-scale vegetable farmers; (iii) design supply-chain management training for aggregator companies; (iv) design post-harvest handling and packaging training for small-scale producers; and, in the long term, (v) support the TVET system in developing a fully-fledged horticultural production training curriculum.

The study provides, in addition, cross-sector recommendations to: (i) strengthen dialogue and collaboration between policy makers, the industry and training institutions with a view to enhancing needs-based skills development; (ii) strengthen the capacity of training institutions involved in agriculture and agro-processing to deliver demand-led skills training; and (iii) support firms in improving their export competitiveness and enhance the competency levels of existing workers.

Source: Extracted from ILO (2016)

4.4 Big data: Emerging approaches based on online information availability

Big data analytics have the potential to map skills by occupation, to identify obsolete skills and discrepancies in skills, and to do predictive analysis of the demand for new occupations and new skills in quasi real-time. They provide quicker and more refined insights than traditional survey-based methodologies (Mezzanzanica and Mercorio, 2019). Big data are useful instruments for skills assessment and anticipation that rely on web sourcing, combined with text mining and machine learning approaches, to collect and classify data on skills, vacancies, technology, and other domains. They can serve to replace or complement traditional data and are usually extracted from job portals, CVs, social media, patents, and scientific databases (Cedefop, 2021b).

Big data provide advantages for skills foresighting and forecasting. For example, they allow understanding in real-time which technologies are becoming relevant and which skills are emerging within existing jobs and occupations, or correlated with the use of a specific technology. The only requirement is that big data contain the information, even unstructured, on technology and skills. However, big data methods can pose more challenges than traditional skills assessment techniques. Unstructured data classification carries uncertainties and big data are sometimes not representative as it is the case, for instance, with job portals. Also, occupation-specific skills are hard to aggregate and algorithms used to extract and process big data and their website sources tend to evolve. Consequently, observed skills trends might be biased. For all these reasons, participatory methods for skills assessment and anticipation involving stakeholders should complement the use of non-participatory methods like big data in order to come up with realistic views on future skill needs and appropriate policy responses.

Some advanced and developing countries undertook projects at the national level implying the use of big data to assess and meet skill needs. In Austria, big data served to develop Public Employment Services (PES)´s skills taxonomy, in the Netherlands for skills anticipation and matching, in Canada to identify skills associated with the national occupational classification, in Latin America and the Caribbean (LAC) and India to document changes in skills demand through LinkedIn, and in Myanmar to inform TVET policies (ILO, 2020b).

As part of the Technical, Entrepreneurial and Vocational Education and Training (TEVET) policy review conducted by UNESCO in 2018 in Malawi (UNESCO, 2019), the country's biggest job site, that is Myjobo.com, was used to assess the feasibility of big data use for labour market analysis and, in particular, to provide insights on trending jobs in urban areas. Jobsite platforms are increasingly used in Malawi for job posting and application. For instance, the number of users of Myjobo.com doubles every ten months. Malawians also have access to other local job sites, broader African job sites such as jobberman.com, and global platforms like Indeed.com and LinkedIn.com, which offer national, regional, and international jobs.

Mezzanzanica and Mercorio (2019) document the key results of the analysis. Between 2016 and 2018, the most demanded jobs in urban Malawi were accountants, accounts assistants, administrative assistants, finance officers, technical officers, project managers, and project coordinators. As an example, the top skills required for an accountant are knowledge of tax, financial reporting, financial analysis, corporate tax, auditing, budgets, and forecasting. The analysis could be replicated in other African countries, preferably using specific national job sites in addition to African and global platforms.

All in all, big data approaches allow for more frequent and simpler updates of skills demand. While big data are successfully processed and gaining ground in advanced economies, sub-Saharan Africa lags behind for several reasons. Often, big data are costly (licensing fees) and limited by the lack of representativeness of online job markets. The TEVET policy review conducted in Malawi, where the labour market is predominantly informal, provides a typical example of the lack of representativeness of big data, a fact commonly observed in low-and middle-income countries. In short, most online job vacancies are for highly qualified workers living in urban areas, and are often even internationally oriented. However, big data approaches have been in development for only a few years. For now, their use in low- and middle-income countries serve mainly to work out feasible implementations in different contexts than high-income countries. Big data approaches are expected to expand and improve, and to become more easily implementable. In addition, the use of the internet for job matching is expected to pick up, even in parts of sub-Saharan Africa where they do not play a role yet. Therefore, big data are increasingly recommended for skills assessment and anticipation.

Administrative records, like education registers tracking students, constitute another source of big data. However, administrative records in sub-Saharan Africa are most often not comprehensive, reliable, updated enough, nor integrated so as to link individuals across different registers, which makes them not suitable to pursue as a source of big data.

To close this chapter, it is worth recalling that skills needs assessment and anticipation are key to prevent imbalances between skills demand and supply. By identifying current and future skill mismatches, they allow individuals and firms to take informed decisions, and public authorities to develop demand-led policy interventions grounded on evidence. Skills needs assessment and anticipation provide essential information for education policy that feeds into qualification frameworks, curricula development, and career guidance. In addition, they serve labour market policy to design or update occupational standards and apprenticeship, retraining and on-the-job training programmes (ILO, 2017; OECD, 2016).

Chapter 5
Existing data sources to analyse qualification mismatch: The prevalence of labour force surveys

Analysing qualification mismatch in sub-Saharan Africa requires adopting a pragmatic approach that acknowledges prevailing data limitations both in terms of availability and quality. As part of this report, we conducted an inventory of existing data sources in sub-Saharan Africa that provide useful information for the analysis of qualification mismatch, with the aim to uncover their strengths and limitations and, ultimately, determine the most relevant ones.

Overall, the data inventory revealed that Labour Force Surveys (LFS) provide the most reliable and detailed information on qualifications and labour market outcomes. Given the prevalence of decent work gaps in sub-Saharan Africa, notably informality and labour underutilization, the analysis of qualification mismatch must draw on data that capture the multifaceted nature of job quality. According to ILO (2013c), decent work indicators are best calculated using estimates derived from LFS.

However, LFS are not available in all sub-Saharan African countries and, when they are, data are not collected on a regular basis. Alternatively, we can resort to household surveys with an employment module but in sub-Saharan Africa, they are conducted irregularly as well. In practice, we most often end up relying on outdated data to analyse qualification mismatch. Another drawback lies in the lack of detailed information on education such as the field of study of graduates from terminal levels of education (i.e., TVET and tertiary education). Furthermore, sample sizes are often not large enough to come up with reliable results for some categories of individuals. In sub-Saharan Africa, this holds true particularly for the most educated. Since household surveys are deemed nationally representative, the small number of observations just reflects prevailing low educational attainment at terminal levels. Notwithstanding these limitations, LFS and household surveys with an employment module are considered the most representative and regular data sources available in sub-Saharan Africa for the analysis of qualification mismatch.

Administrative records – e.g., education registers on students and graduates or statistics on vacancies and job seekers from Public Employment Services (PES) – provide additional information useful for assessing qualification mismatch but they are scarcely available in sub-Saharan Africa. In addition, administrative data are generally of poor quality in the region. As regards PES for example, which are either inexistent or largely underdeveloped in sub-Saharan Africa, their coverage is typically low and services do not reach rural and remote areas, nor the informal economy where the bulk of the labour supply and demand lie (IDB, WAPES and OECD, 2016). Overall, the lack of data collection and administration for statistical needs, together with the large shares of unregistered enterprises and job seekers, make administrative records not suitable for use.

Tracer studies, combined with employer satisfaction surveys, are particularly useful for the analysis of qualification mismatch as they directly link the current employment situation of graduates with their previous educational experiences. Unfortunately, the scarce tracer studies available in sub-Saharan Africa are not regular, systematic, and representative of the population of graduates.

To bridge data gaps and improve the knowledge base on qualification mismatch, some non-exhaustive recommendations follow. First, conduct LFS or household surveys with an employment module on a more regular basis and cover education aspects comprehensively by systematically capturing levels of education, including TVET, fields of study and qualifications. Second, conduct tracer studies and employer satisfaction surveys, even *ad hoc* if regular data collection is too demanding, to complement the information provided by LFS and household surveys with an employment module. Third, collect qualitative data as another complementary source of information, for instance, through workshops, focus groups, and in-depth interviews with key experts and stakeholders.

In the rest of the chapter, we provide a brief description of the main data sources to measure qualification mismatch, and more broadly to undertake skills assessment and anticipation.

5.1 Labour force surveys, household surveys with an employment module and population censuses

Labour force surveys (LFS) are considered the most appropriate source of data to analyse access to employment, quality of jobs, and the multiple dimensions of decent work (ILO, 2013c). By providing information on the level of education and the main occupation of workers, based generally on the ISCED and ISCO classifications, they allow in particular measuring vertical qualification mismatch. Measuring horizontal qualification mismatch requires information on the field of study, which is not systematically available in the LFS conducted in sub-Saharan Africa. In the absence of LFS, household surveys with an employment module can be used.

LFS and household surveys with an employment module have the potential to capture informal workers, but they sometimes fail to cover rural and remote areas, and people who do not live in ordinary households such as migrants (Říhová and Strietska-Ilina, 2015). In sub-Saharan Africa, both types of survey need to be conducted on a more regular basis to uncover recent trends, and draw on larger sample sizes to obtain more robust data and detailed breakdowns.

Population censuses may also be used to analyse qualification mismatch, provided they contain enough information on education and the labour market (i.e., occupation, sector of activity, level and field of education). However, population censuses are not as detailed and accurate as LFS and household surveys with an employment module, and their use is severely limited by the low frequency of data collection, usually once every ten years, and the lengthy data processing before results are made available (ETF/CEDEFOP/ILO, 2016a). *Table 2* below lists the main strengths and weaknesses of LFS, household surveys with an employment module, and population censuses.

Table 2 Strengths and weaknesses of labour force surveys, household surveys with an employment module and population censuses

Data source	Strengths	Weaknesses
Labour force surveys (LFS) and household surveys with an employment module	*In general:* • Provide structural information on individuals (age, gender, education, occupation). • Have the potential to cover informal employment. *In the sub-Saharan African context:* • Household surveys with an employment module can be used to retrieve labour market information when LFS surveys are not available.	*In general:* • Costly. • Usually do not cover the population living outside households. • Covering remote areas may be difficult; some countries include only the urban population. • Large sample sizes are required to obtain robust data and enable detailed breakdowns. • Political implications (difficulty in getting reliable information in countries with high ethnic or racial tensions). *In the sub-Saharan African context:* • Not available in all countries; • Not regularly conducted (outdated data).
Population censuses	*In general:* • Comprehensive information on population size and basic demographics. • Can provide data on small occupational groups and small geographic areas.	*In general:* • Low frequency. • Long process of administration before data are released. • Usually not enough labour market information. • Key labour force concepts such as employment and unemployment may be measured with less accuracy than in LFS. • Quality of occupation, industry and qualifications coding may be poorer than in official household surveys. • Political implications. *In the sub-Saharan African context:* • Not regularly conducted (outdated data). • Do not provide detailed information on qualification mismatch compared to LFS and household surveys with an employment module.

Source: ETF/CEDEFOP/ILO (2016a).

5.2 Skill-specific data sources

Skills-specific data sources such as establishment skills surveys and tracer studies provide key information for the analysis of skill mismatch. They have the advantage of directly measuring skills rather than proxying them by qualifications. However, they are scarcely available in the context of sub-Saharan Africa. Where quantitative information is either unavailable or insufficient, qualitative methods can be used to collect data on skills. *Table 3* below summarizes the main strengths and weaknesses of these skill-specific data sources.

Establishment skills surveys provide information on skill needs, skills gaps, vacancies, and training activities as reported by employers. They are useful for anticipating skills supply and demand and addressing more qualitative information about the skills needed by employers and the skills gaps they face (ETF/CEDEFOP/ILO, 2016a). The weakness of these surveys is that often employers do not have detailed information on skill needs, and supervisors who may have this information are difficult to reach. Also, the coverage of establishment skills surveys is generally restricted to specific economic sectors and exclude informal sector enterprises and micro-businesses, which employ the majority of workers in sub-Saharan Africa. There exists, however, some establishment surveys covering informal production units, like the 1-2-3 surveys, which focus in phase 2 on unregistered businesses operated by self-employment workers. Establishment skills surveys should have information on why it is hard to fill vacancies and document the different types of skill shortages and training needs (Říhová and Strietska-Ilina, 2015).

A tracer study, also called graduate survey, alumni survey or graduate tracking, is a standardized survey taking place after or at the end of a study or a training programme (ETF/CEDEFOP/ILO, 2016c). It targets graduates normally between six months and three years after graduation. Tracer studies are informative for skills assessment and anticipation because they provide information on study progress, graduates' transition to work, work entrance, job career, learned competencies, current occupation, and bonds to the education institution. Since tracer studies only cover early experience in the labour market, relying on them for the analysis of skill mismatch can lead to biased results; hence, they must be treated with caution. In the absence of tracer studies, the ILO School-to-Work Transition Surveys (SWTS) conducted in some sub-Saharan African countries[12] can be used. These surveys cover a representative sample of young people aged 15 to 29 years, including graduates; provide retrospective information on labour market transitions; and allow measuring various forms of skills mismatch. See ETF/CEDEFOP/ILO (2016c) for comprehensive information on how to carry out tracer studies, and ILO (2019) for a detailed analysis of skill mismatch using SWTS data.

Some surveys are specifically designed to assess skills and include questions for workers and their employers on skill requirements, like the OECD Survey of Adult Skills (Programme for the International Assessment of Adult

12 Benin, Congo (Rep.), Liberia, Madagascar, Malawi, Tanzania, Togo, Uganda, and Zambia.

Table 3 Strengths and weaknesses of skill-specific data sources

Data source	Strengths	Weaknesses
Establishment skills surveys	*In general:* • Opportunity to get direct information at the company level.	*In general:* • More informative for the current situation than the future. • Limited possibilities for obtaining information on individuals. • No information on the population out of employment. *In the sub-Saharan African context:* • Informal production units not covered while they employed the majority of workers.
Tracer studies	*In general:* • Relatively low cost; • Easy execution.	*In general:* • Demand for detailed information about sample groups. • Only cover early market experience, so findings may be biased. *In the sub-Saharan African context:* • Scarcely available; • Not regular, systematic, and representative of the population of graduates.
Qualitative data on skills	*In general:* • Relatively cheap and easy to implement compared to quantitative surveys. • Can be focused specifically on skills. • Can bring more understanding of the underlying causes and processes. • As a secondary benefit, can facilitate engagement of the actors. *In the sub-Saharan African context:* • Can complement the lack of quantitative data. • Useful to analyse skills in the informal sector.	*In general:* • Subjective; • Risk of over-emphasising marginal issues; • Partial, do not provide comprehensive information.

Source: ETF/CEDEFOP/ILO (2016a).

Competencies [PIAAC]) and the World Bank Skills Towards Employability and Productivity (STEP) Skills Measurement Surveys. Unfortunately, PIAAC surveys are not conducted in Africa and STEP surveys only cover two sub-Saharan African countries, namely Ghana and Kenya. STEP surveys provide policy-relevant data to better understand skill requirements in the labour market, as well as backward linkages between skills acquisition and educational achievement, personality traits and social background. These surveys assess three different categories of skills: (i) cognitive skills (reading, writing, and numeracy); (ii) socio-emotional skills, including personality traits (openness, conscientiousness, extraversion, agreeableness, neuroticism, and grit), behaviour (hostile attribution bias and decision making), and risk and time preferences; and (iii) job-relevant skills, including qualifications required for the job and skills used at work (autonomy and repetitiveness, computer use, contact with clients, solving and learning, supervision and physical tasks) (Pierre et al., 2014). The STEP Programme, which includes a household-based survey and an employer-based survey, provides a good example of linked employer-employee skills surveys.

Qualitative information collected, for example, through literature reviews, workshops, focus groups and in-depth interviews with experts and key stakeholders, are useful to complement the quantitative information obtained through surveys and help fill some knowledge gaps. However, qualitative data need to be backed by empirical evidence to limit the subjectivity bias and the risk of overemphasizing marginal issues.

5.3 Administrative records

Data from administrative records can also serve to assess qualification mismatch but they are scarcely available in sub-Saharan Africa and generally of poor quality. The lack of data collection and administration for statistical needs make administrative records in the region most often not suitable for use. T*able 4* below provides some insights into the strengths and weaknesses of the most relevant administrative data for the analysis of qualification mismatch, that is, Public Employment Services (PES) statistics on vacancies and job seekers, enterprise statistics and education statistics.

Table 4 Strengths and weaknesses of administrative records

Data source	Strengths	Weaknesses
Public Employment Services (PES) statistics on vacancies and job seekers	*In general:* • Use of existing data, no need for additional data collection. • Administrative regional data, no sampling issues. • Potential for high quality and detailed information on occupations, qualifications, and skills in demand.	*In general:* • Only flows, no information on stocks. • Usually cover only a specific segment of the labour market. *In the sub-Saharan African context:* • PES either inexistent or largely underdeveloped. • Low coverage: PES do not reach rural and remote areas, nor the informal economy where the bulk of the labour supply and demand lie. • Few vacancies and job seekers are registered due to the lack of unemployment benefits and the low PES coverage (workers and employers mostly resort to private and informal channels).
Enterprise statistics	*In general:* • Direct information from companies. • Complementary source to household statistics. • Can link employment trends to business trends.	*In general:* • Require developed infrastructure at the statistical institute as well as company level (human resources databases of companies, registry of companies). • Do not cover the informal economy and informal employment. • Often do not cover SMEs or some sectors. *In the sub-Saharan African context:* • Predominance of the informal economy: most businesses are not registered with competent authorities and therefore not captured by enterprise statistics.
Education statistics	*In general:* • Use of existing data – no need for additional data collection. • No sampling error – the possibility of detailed breakdowns.	*In general:* • Inform about potential supply but do not provide information on what is happening with graduates in the labour market. *In the sub-Saharan African context:* • Consolidated and up-to-date comprehensive data on terminal levels (TVET and tertiary education) rarely available.

Source: ETF/CEDEFOP/ILO (2016a).

PES statistics can potentially provide reliable and detailed information on occupations, qualifications, and skills in demand, but in sub-Saharan Africa they are either inexistent or largely underdeveloped. The PES coverage in the region is typically low, with services not extending to rural and remote areas, nor to the informal economy where the bulk of the labour supply and demand lie. In addition, job seekers have little incentive to register with PES if they are not provided with unemployment benefits. PES statistics are far from representative of the labour market in sub-Saharan Africa given the prevalence of unregistered job seekers and enterprises who typically resort to informal channels to find work and fill vacancies.

Enterprise statistics provide information reported by employers on production, export and other topics, including employment, workers' education and skills, and wages. They are used as a main source of employment data in some developed countries (ETF/CEDEFOP/ILO, 2016a). In sub-Saharan Africa, enterprise statistics are much less relevant because they exclude micro and small businesses, and the informal economy. They are even difficult to compile for formal sector enterprises because they require a well-documented registry of companies.

Education statistics obtained from administrative data on students and graduates are instrumental in the quantification and characterization of skills supply. They are usually produced as part of the Educational Management Information System (EMIS) and compiled in statistical yearbooks. In sub-Saharan Africa, the main problem relates to the lack of comprehensive statistics on terminal levels of education (TVET and tertiary studies) and on the external efficiency of the education system (labour market transitions of former students and graduates). Moreover, administrative data on education are often not consolidated and up to date, which explains why LFS and other household survey data are often preferred to analyse skills supply.

Chapter 6
Conclusion and the way forward: A stepwise approach to measuring qualification mismatch

This report aimed to provide policy makers, development practitioners, and researchers with the necessary tools for analysing qualification mismatch in sub-Saharan Africa. It went beyond existing frameworks by taking into account data constraints and the labour market context pertaining to the region. The report adopted a pragmatic approach by focussing on qualifications given the scarcity of available data on skills, and presented a set of key indicators that allow a quantitative assessment of qualification mismatches based on the most reliable and representative data commonly collected in sub-Saharan Africa.

Overall, sub-Saharan African countries have limited statistical capacity and data resources. Most often, they rely on labour force surveys or other household surveys with an employment module for labour market and qualification mismatch analyses. Skill-specific surveys are rare and limited to one-off data collection exercises. Besides, informal employment is widespread in sub-Saharan African labour markets and traditional indicators like the unemployment rate fall short of providing a comprehensive picture of labour underutilization.

Given data limitations, this report recommends conducting regular updates of qualification mismatch indicators based on the normative and empirical methods, to be disaggregated and analysed for various categories of individuals in order to evidence those most at risk. In the context of sub-Saharan Africa, it is also recommended to provide regular updates of core labour market indicators on labour underutilization and informal employment, broken down in particular by qualification, occupation and sector of activity. This basic set-up allows documenting key elements of labour supply and demand and imbalances occurring in the labour market.

In addition, all specific data or research on skills should be collected and made available for secondary analysis, a good practice already adopted in several international projects,[13] in order to provide insights into the causes and consequences of skills mismatch. Since these *ad hoc* data become quickly outdated and are usually limited to specific populations, the core labour market indicators should provide a backdrop against which such a secondary analysis could be undertaken.

Skills needs anticipation requires even more analytical capacity and, in quantitative form, data that is generally beyond the resources available in sub-Saharan Africa. Consequently, we recommend concentrating on collecting and analysing current qualification mismatches rather than investing heavily in forward-looking instruments. If needed, forward-looking analyses could be based more easily and with less quantitative demands on foresighting exercises that provide a similar rigour at a sectoral level, such as in the methodology developed as part of the ILO's Skills for Trade and Economic Diversification (STED) Programme.

13 In particular, the OECD Programme for the International Assessment of Adult Competencies (PIAAC) and the World Bank's Skills Towards Employability and Productivity (STEP) Programme.

Consideration should also be given to the institutionalization of qualification mismatch measurement and analysis, which would serve two purposes. First, it would provide an institutional setting to gather different analyses together, build up the capacity to provide insights geared towards the national context, and provide some assurance of regular updates of the indicators and their analyses. Second, as skills assessment and anticipation have multiple purposes and serve to inform a wide range of labour market actors, such an institutionalization would also provide the setting for the integration of various stakeholders and their feedbacks into the discussions. The latter would allow for a policy-oriented interpretation of analytical results in the area of education and labour market policy, and in supporting education and training providers to make effective use of these results.

Common data challenges relating to the development and implementation of skills assessment and anticipation tools include: (i) the measurement of skills (rather than qualifications and occupations); (ii) data availability and accessibility; (iii) data frequency, reliability, and level of detail; and (iv) the capacity to use and analyse the data correctly. Social dialogue is important to support and sustain ongoing efforts. To be demand-responsive, policy makers, education and training providers, and other key stakeholders need to know what skills are in demand, and how they will evolve over time. They should use this information to adapt policies and training provisions, which requires effective mechanisms to collect, analyse, disseminate and apply knowledge on the demand for and supply of skills. In many low- and middle-income countries, these mechanisms are flawed or non-existent.

To conclude, we recommend adopting the general stepwise approach described below to measure qualification mismatch and, by extension, to conduct skills assessment and anticipation.

Step 1. Collect key information on qualifications and the labour market. The analysis of qualification mismatch draws essentially on data obtained from labour force surveys and other household surveys with an employment module. These surveys must be representative at the national level, conducted on a regular basis, and provide detailed information on qualifications and the characteristics of jobs. Survey questionnaires should follow ILO recommendations for the identification of qualification mismatches and other labour market conditions that are correlated such as labour underutilization and informality. In addition, survey samples should be large enough to allow the necessary breakdowns for profiling mismatched workers. Once collected, it is equally important to make the data available to key users that process and analyse them.

Step 2. Construct and analyse core labour market and qualification mismatch indicators. While data is often available, processing the various datasets to provide the necessary information at a level that policy makers can understand is key in preventing and addressing qualification mismatches. In this report, we have proposed a set of core labour market and qualification mismatch indicators, based not only on their relevance and availability in the sub-Saharan African context, but also on their simplicity to allow countries computing and interpreting them easily.

Step 3. Enrich the analysis with additional data sources. When available, other sources of data than labour force surveys or household surveys with an employment module can be used to deepen the analysis, for example, by considering specific groups (e.g., young people with the ILO School-to-Work Transition Surveys [SWTS]), specific needs (e.g., employers' needs with establishment skills surveys), or specific issues (e.g., informality with the second phase of 1-2-3 surveys). Most importantly, skill-specific data sources must be used in order to complement the analysis of qualification mismatch by direct measures on skills. In sub-Saharan Africa, when these additional data sources exist, they most often come from donor-sponsored projects. It is important to provide access to the rich labour market information these data sources contain.

Step 4. Extend the analysis to skills anticipation: Once qualification mismatches have been evidenced and analysed based on existing data, a step towards the analysis of future skills needs and imbalances can be made. As discussed in this report, quantitative skills forecasting is too demanding in terms of data for sub-Saharan African countries. In addition, it requires a forecasting capacity that is currently lacking. Therefore, it is probably not the most appropriate forward-looking approach to consider at present. In practice, skills anticipation based on establishment skills surveys and eliciting short-term skill demand is commonly used to come up with quantitative data reflecting future skills imbalances. Other potentially interesting skills anticipation methods for sub-Saharan Africa are within the realm of big data using online job sites to document the evolution of the demand for skills. However, these methods are still under development and will take time to mature into usable instruments. Besides, current labour markets in sub-Saharan Africa are not well represented in online job sites, including in national ones. At least, online job sites are expected in the future to improve the coverage of medium- and high-skilled job vacancies, and will thus constitute a useful source of big data for these particular segments of the labour market. Finally, skills foresighting, especially when grounded in data and analyses of the current skill mismatches and labour market issues, seems to be the most convenient approach to envision the future and anticipate potential skills imbalances to come.

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The present report aims to provide policy makers, development practitioners, and researchers with the necessary tools for analysing qualification mismatches in sub-Saharan Africa. It goes beyond existing frameworks by taking into account data constraints and the labour market context pertaining to the region.

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