RESEARCH STREAM
Addressing Africa's youth unemployment through industries without smokestacks

March 2020

Employment creation potential, labor skills requirements, and skill gaps for young people

A methodological framework

Haroon Bhorat, Caitlin Allen, Zaakhir Asmal, Robert Hill, and Christopher Rooney

Africa Growth Initiative
at BROOKINGS

AGI Working Paper #25

Haroon Bhorat is director of the Development Policy Research Unit (DPRU) at the University of Cape Town and a nonresident senior fellow at the Africa Growth Initiative at the Brookings Institution.

Caitlin Allen is a research analyst at DPRU.

Zaakhir Asmal is senior research analyst at DPRU.

Robert Hill is a research analyst at DPRU.

Christopher Rooney is a research analyst at DPRU.

Acknowledgements

The authors gratefully acknowledge very helpful comments from Homi Kharas, Tim Gindling, Ragui Assaad, John Page, Richard Newfarmer, Brahima Coulibaly, and the other participants in the Brookings Institution workshops on addressing youth unemployment through industries without smokestacks.

Brookings gratefully acknowledges the support provided by the Mastercard Foundation and Canada's International Development Research Centre (IDRC). Brookings recognizes that the value it provides is in its commitment to quality, independence, and impact. Activities supported by its donors reflect this commitment. The views expressed by Brookings do not necessarily represent those of the Mastercard Foundation or its Board of Directors, or IDRC or its Board of Governors.

Contents

Abstract

This paper presents a methodological framework for assessing the extent to which youth unemployment can be addressed through employment creation in industries without smokestacks in individual countries, as well as the skill gaps in the youth population that need to be addressed for this potential to be reached. There are two components to the method: (i) estimating skill demand, and (ii) identifying skill gaps in the target youth population. On the labor demand side, the framework seeks to identify the skills required for a sector to reach its employment potential. On the supply side, the methodology ultimately aims to answer the question: *Do the skills to meet the demand in the sector exist in the population; and if not, where are the gaps?*

On the demand side, we first present a number of methods to estimate potential employment in a sector that make use of measures of labor force intensity for a sector, such as labor-value added ratios and employment elasticities. We also present an alternative global value chain-based approach that considers how future employment in a sector may be greater than projected employment in a sector. This approach, however, requires the extensive use of surveys and in-depth sectoral research The framework has a strong emphasis on the occupational requirements of sectors, and, based on the assessment of potential employment in the sector, we then present methods for determining the occupational requirement profile of the sector. A skill requirement profile is then obtained using this occupational profile. This profile relates the set of occupations required for the sector to reach its employment potential to a measure of skill such as education.

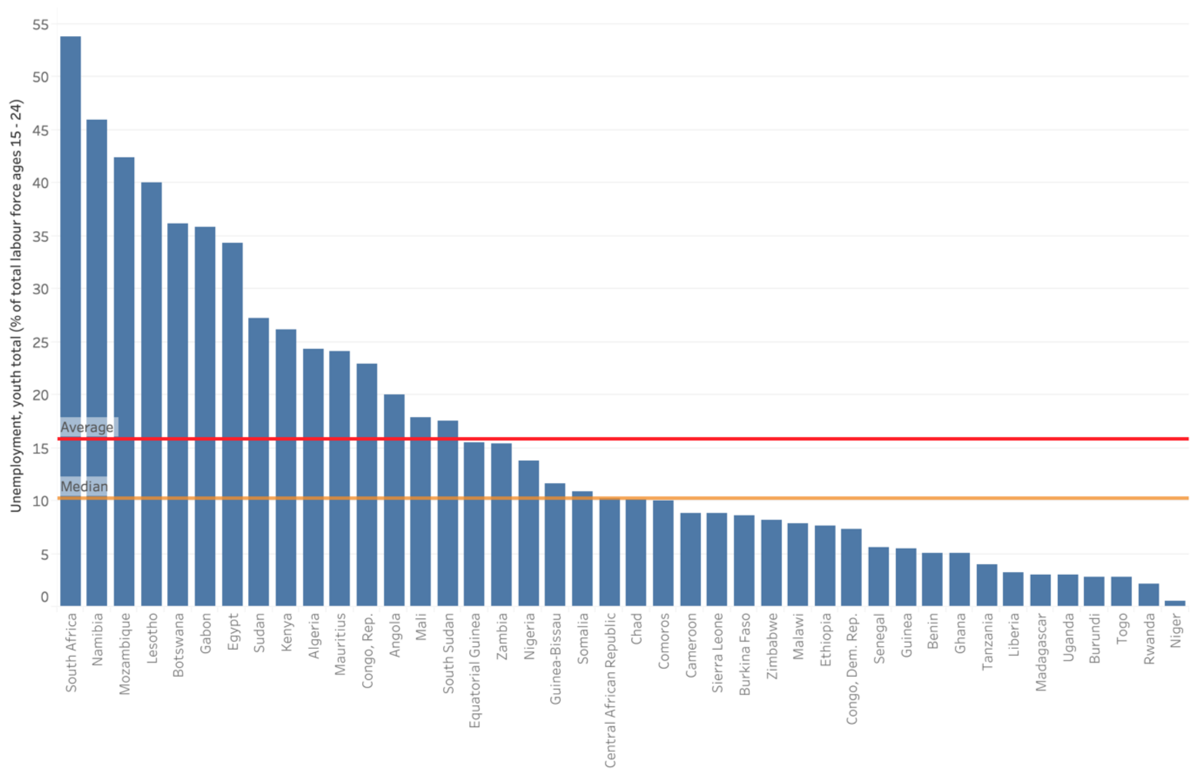
On the supply side, the framework uses the skill requirement profile for the sector to consider whether the skills to meet a sector's skill requirements exist in the youth population; and where the youth may currently be lacking in respect of the skills required by the sector. We identify two types of skill gaps. The first is a sectoral skill gap, an indication of the gap between the set of skills available in the population and the set of skills required by the sector. The second is an occupational skill gap identified for key occupations that relates the skill requirement for each occupation to the skill level of the average unemployed youth. Both these gaps are important for assessing the extent to which there is currently a skill deficit in the target population for any particular sector, and taking appropriate action to address that gap so that the youth can attain the skills to be able to participate in the sector, as well as to enable sectors to reach their potential.

1. Introduction

A new pattern of structural change is emerging in Africa, characterized by higher growth rates in the services sectors relative to manufacturing—a pattern in contrast to the manufacturing-led transformation of East Asia. Page (2018), for example, notes that between 1998 and 2015, services exports grew more than six times faster than merchandise exports across Africa. With the advent of technology and the trend towards a completely integrated global economy, certain sectors have risen to the fore in terms of their relative importance for economic development in African countries. These industries—dubbed "industries without smokestacks" (IWOSS)—include, for example, information and communications technology (ICT)-based services, tourism, and transport (Brookings, 2018). Examples include vibrant ICT-based sectors in Kenya, Rwanda, Senegal, and South Africa. Indeed, tourism accounts for 30 percent of Rwanda's and 3 percent of South Africa's GDP. Similarly, there are high levels of integration and participation of countries such as Ethiopia, Ghana, Kenya, and Senegal in global horticultural value chains (Page, 2018).

These industries present an opportunity for African economies to address high and growing rates of unemployment, among the youth in particular. Figure 1 below shows the unemployment rate of youth (aged between 15 and 24) in 42 sub-Saharan African countries in 2018. Across the sample of 42 countries, the average rate of youth unemployment, represented by the red line in the figure, is 15.9 percent, and the median rate, represented by the orange line, is 10 percent. Notably, it is as high as 55 percent for South Africa and greater than 20 percent for 12 other countries in the sample.

Figure 1. Unemployment rates of youth (15 -24 years old) across Africa



Source: World Bank (2018).

In this paper, we present a methodological framework for assessing the extent to which youth unemployment can be addressed through employment creation in these industries without smokestacks in individual African countries, and the skills required for individuals to be absorbed into these industries.[1] While we focus specifically on four of these industries (tourism, horticulture, agro-processing, and transit trade), this framework will be readily applicable to other sectors as well.

Section 2 presents the conceptual framework for the method and includes a note on how we approach identifying the required data for each of the four sectors under consideration. We note, in particular, the specific challenges and limitations we may face with respect to these four sectors. Thereafter, we proceed with an overview of the proposed methodological framework. The methodological framework consists of two broad components. The first component (presented in Section 3) is focused on employment potential and details methods to assess the employment creation potential of a sector. It also considers how estimates of employment potential can be used to obtain an occupational requirements profile for a sector. The second (Section 4) focuses on identifying skill gaps for youth, and initially lays out methods to assess the labor skills requirements of a sector to reach its potential. It then describes how this skills requirement profile can be used to identify skill gaps for young people in relation to the sector. Section 5 concludes and summarizes the methodology.

2. Conceptual framework

2.1 Identifying skill gaps

There are two main methodological components present in this paper: 1) estimating sectoral skill demand, and 2) identifying skill gaps in the target population in line with that demand. In terms of labor and skills demand, we aim to estimate potential employment, occupational requirements, and skill requirements for a particular sector. For our understanding of labor and skills supply, we aim to identify skill gaps for the youth in line with the estimate of potential employment. The occupational profile obtained from the estimate of potential employment is the key link between the demand and supply sides, as it is derived from the potential employment estimate used as an input to obtain an estimate of skills requirements for an industry. Our ultimate aim is to determine the gap between the skills required for the occupations identified through the employment potential component of the exercise on the demand side, and the skills available in the target population on the supply side (i.e., youth).

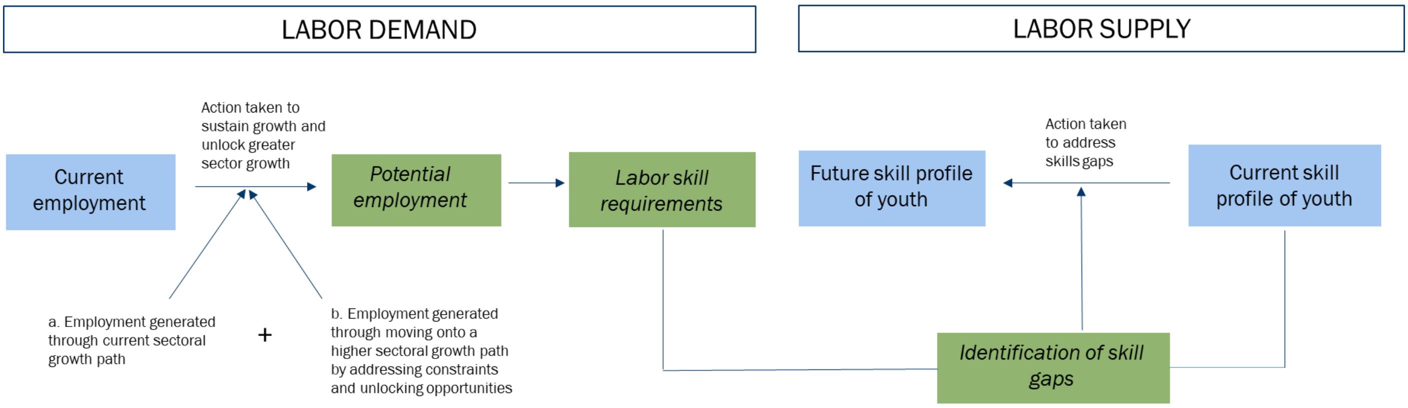
On the demand side, we ultimately aim to answer the following question: *What skills are required for the sector to reach its employment potential?*

For a particular sector, the starting point for the exercise is to understand the *current demand for labor* in the sector, and how this can be projected to shift in the future. One method of estimating this **potential employment** is to assume that employment growth in the sector continues to grow in line with past performance and the prevailing labor intensity of output in the sector. However, understood more broadly, future employment may also be greater than that projected based on current demand and trends in demand—in short, if constraints to growth in the sector are addressed and opportunities for growth in the sector are unlocked. We thus also consider how **potential employment** measured in this regard can be estimated so that the appropriate skills to achieve this growth can be planned for—and not only the skills requirements for maintaining the current steady state growth path of the sector. Methods for estimating potential employment thus consist of two possible approaches: One that projects employment based on current demand and

[1] It should be noted that although this paper focuses mainly on skills and skill gaps, it is not to say that other factors do not influence the employability of youth. In fact, it is possible that other factors, such as access to the labor market, act as greater barriers to youth employment than a lack of skills, however, investigation of these non-skill related factors lies beyond the research agenda of this paper.

historical trends, and one that considers how employment growth can be unlocked through appropriate improvements in "upgrading" in the sector.

Figure 2. Employment creation potential and the identification of skill gaps for young people for a particular industry



Note: Our methodological framework does not encompass the formulation of relevant policy and implementation actions for a sector to reach its potential or for the identified youth skill gaps to be addressed. The framework suggests methods for assessing potential employment, industry skills requirements and skill gaps only.

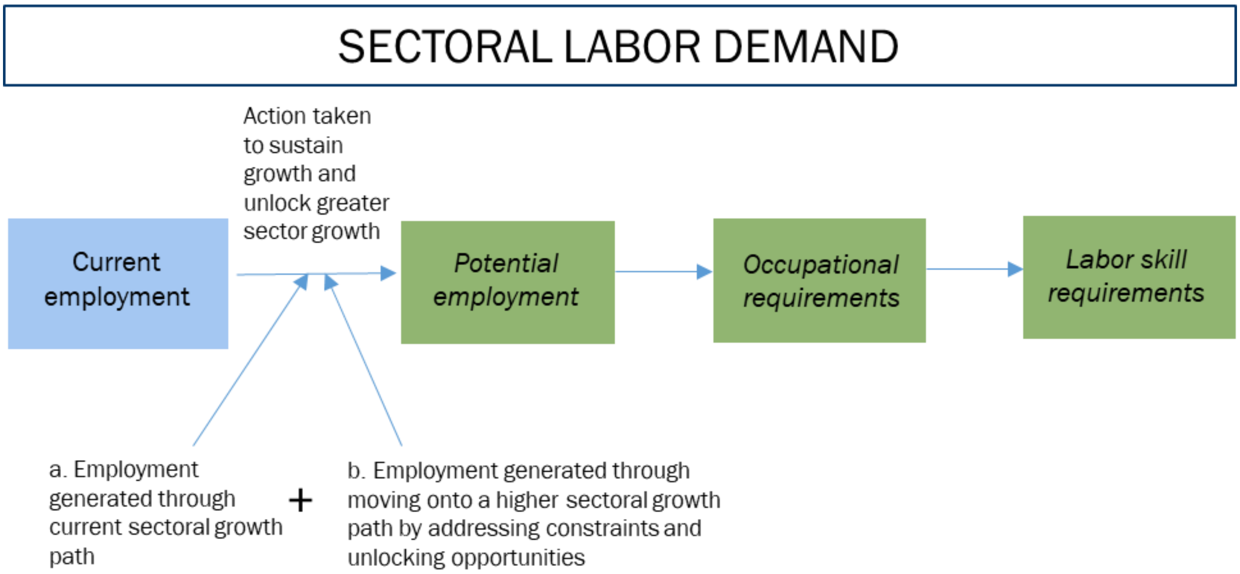
Our approach places a strong emphasis on the occupational requirements of sectors. The potential employment estimated in the first stage of the method is thus used to estimate a **profile of occupations** for the sector, in line with the estimated potential employment, which can be used for the purposes of identifying skills requirements for the sector and skill gaps for individuals. In this regard, either a list of relevant occupations for a sector to reach its employment potential can be estimated as the profile, or the exact number of individuals per each occupation required for the sector to reach its potential can be estimated as the profile.

While, ideally, we would want to obtain an estimate of the second, more granular occupational profile, data and operational constraints may mean that it is not feasible to obtain such precise estimates of the distribution of occupational requirements of the sector. We therefore also present the first limited occupational profile as an alternative. In our method, we further note the implications of using either of these profiles for the purpose of estimating skill gaps.

Having understood the potential employment trends of the sector and the occupational profile in line with this, we proceed to the second component of the method that focuses on skills. We first consider the labor skills requirements for the sector to meet projected future demand obtained from the estimate of potential employment. The **skills requirement profile** is based on the occupational profile, and relates the set of occupations required for the sector to reach its employment potential to a measure of skills such as education. We expand on this in the Skills Requirements section of the method.

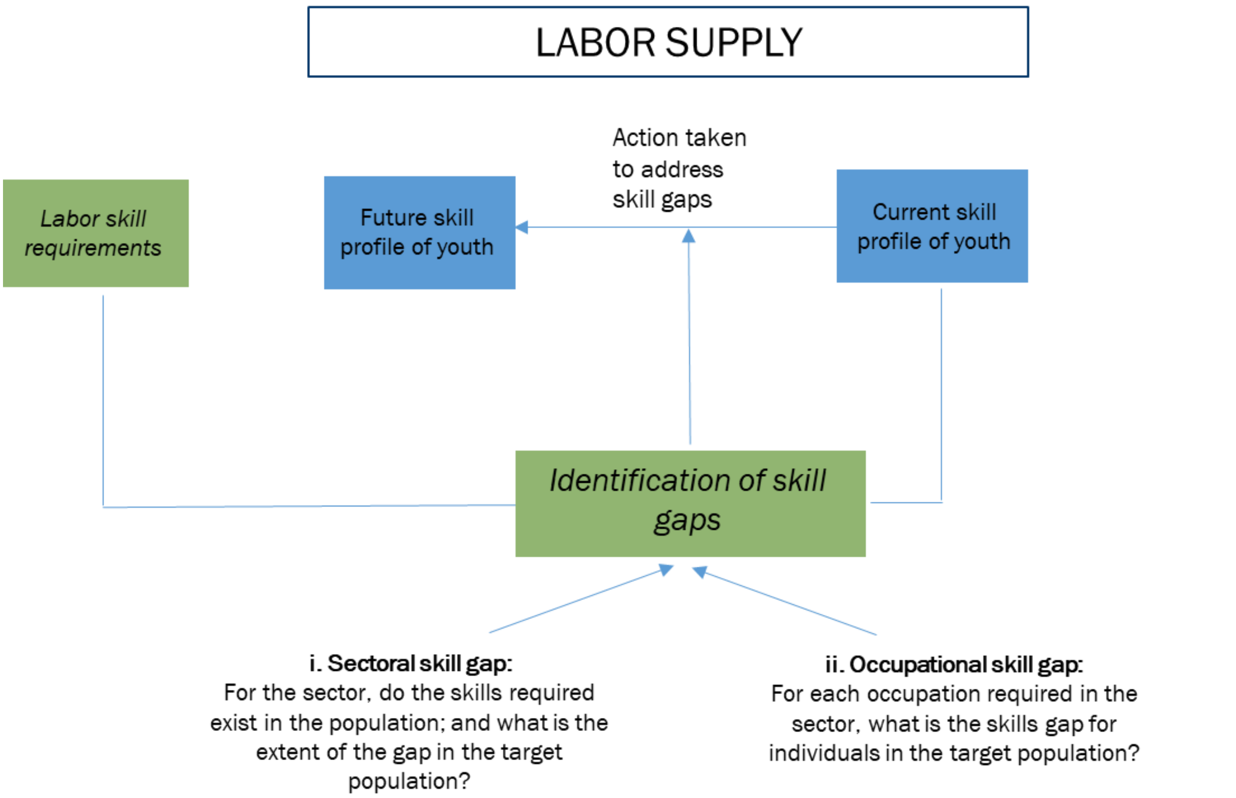
The potential employment, occupational profile, and skills requirements estimations form part of the **labor demand** component of the method. This component of the method is focused at the sectoral level, and ultimately provides us with a skills requirement profile based on the potential employment estimate. This stage of the process, at the sectoral level, can be represented by the labor demand side of Figure 2 above and in more detail in Figure 3 below.

Figure 3. Potential employment informing sectoral skills demand



Having determined the demand for skills in the sector, we turn our attention to the supply of skills and aim to answer: *Do the skills to meet the demand exist in the target population; and, if not, where are the gaps?* Skill gaps arise when employers cannot find suitably skilled workers from the external labor market to fill open positions (Frogner, 2002; and OECD, 2017). Using the skills requirement profile for the sector, we consider whether the skills to meet these requirements exist in the target population (youth), and estimate **skill gaps** based on a comparison of this sector's occupation-defined skills profile to the skills profile of the youth population.

Figure 4. Identification of skill gaps for the youth



Before discussing methods to obtain these estimates—and ultimately identify the skill gap for youth with reference to any particular industry—we start with a description of how we identify the four sectors under consideration within the available data. While some of these sectors are easily identifiable within standardized industry coded data, in the cases of some of the sectors it may be more difficult to obtain data pertaining specifically to the sector. We discuss how we approach identifying all four of these sectors under consideration in the following section, before proceeding to discuss the proposed methodologies.

2.2 Identifying Industries Without Smokestacks in Data

Most of the methods laid out in this paper (e.g., identifying the skills, occupations, and education profiles for individuals employed in a specific sector) crucially depend on being able to isolate individuals employed in a particular sector. This section outlines the extent to which it is possible to do so for each of the four sectors of interest in this project.

2.2.1 Agro-processing

The Food and Agriculture Organization (1997) defines agro-processing as "a subset of manufacturing that processes raw materials and intermediate products derived from the agricultural sector." From this definition, the following sectors are typically considered part of the agro-processing sector: beverages, food, footwear, furniture, leather and leather products, paper and paper products, rubber products, textiles, tobacco, wearing apparel, and wood and wood products.

The agro-processing industry is particularly important for countries hoping to undergo structural transformation, as it has strong backward and forward linkages to other key sectors. Backward linkages include the agriculture industry and capital equipment manufacturers, while forward linkages include the packaging and transport industries.

Table 1 shows the relevant 3-digit Standard Industrial Classification (SIC) codes along with descriptions of the codes.[2] As these 3-digit codes are easily identifiable in our dataset, we are confident that these sub-sectors can provide precise estimates of the size and employment potential of the agro-processing sector.

Table 1. SIC codes and descriptions for agro-processing (3-digit level)

SIC code	Sub-sector
301 - 304	Food
305	Beverages
306	Tobacco
311 - 312	Textiles
313 - 314	Wearing apparel
315 - 316	Leather and leather products
317	Footwear
321 - 322	Wood and wood products
323	Paper and paper products
391	Furniture

Source: Food and Agriculture Organization (1997).

[2]Standard Industrial Classification is a system used to classify industries. The SIC system is hierarchical, with a greater number of digits indicating a narrowing of a particular category. For example:

42 Trucking and warehousing
421 Trucking and courier services, excluding air
4212 Local trucking, without storage

2.2.2 Horticulture

Horticulture can be defined as the "cultivation, processing, and sale of fruits, nuts and vegetables, ornamental plants, and flowers as well as many additional services" (Shyr & Reilly, 2017). Other products typically associated with the horticulture industry are coffee, tea, cocoa, spice crops, nuts, and dates.

The horticulture industry has increased in importance over the past few decades because of an increased focus on "healthy living," especially in developed countries. Most horticultural products contain a range of nutritional compounds essential to healthy living. Furthermore, because horticulture is a knowledge-intensive sector—requiring the use of sophisticated management practices to protect horticulture products from diseases—it is a sector in which developing countries can identify potential opportunities to move up the value chain through the production of higher-value products.

A measurement of the horticulture sector has been provided by a training institution for the agricultural sector in South Africa. This institution identified 9 SIC codes that relate to horticulture (AgriSeta, 2018), displayed in Table 2.

Table 2. SIC codes and description for horticulture (5-digit level)

SIC code	Sub-sector
11120	Growing of vegetables, horticultural specialties and nursery products
11121	Ornamental and nursery products
11130	Growing of fruit, nuts, beverage, and spice crops
11301	Growing of coffee and tea including coconuts, cocoa, nuts, olives, dates, etc.
12109	Growing of trees as second crop by farmers
30132	Fruit packed in cartons, fruit juice concentrate drummed and fruit juice in container
30133	Fruit exporters and importers
30493	Processing and marketing of coffee and tea including coconuts, cocoa, nuts, olives, dates etc.
62112	Service to nut farmers and companies

Source: AgriSeta (2018).

However, these codes are at the 5-digit level. We note here that the relevant survey data may not be available at this level in many countries. If we are only able to access industry data at the 3-digit level, we can use two 3-digit codes which are relevant for an estimation of the horticulture industry: 111 (growing of crops, marketing gardening and horticulture) and 301 (production, processing and preserving of meat, fish, fruit, vegetables, oils and fats). Unfortunately, we will lose a degree of detail if we do this. In this case, our estimate of the size of the horticultural sector and number of individuals employed in the sector will likely be an overestimate compared to the estimate that would be obtained if we were able to use the 5-digit level codes.

2.2.3 Transit trade

Transit trade refers to "the business connected with the passage of goods through a country to their destination" (Free Dictionary, 2019). No formal definition seems to exist for transit trade in the economic literature. Evidently, however, the term seems to refer to a type of trade that has become possible due to the invention of mass transportation; particularly trucks, railways, and ships. According to this definition, however, it is difficult to identify industries specifically related to transit trade.

As a compromise, we can identify 3-digit SIC codes that are most closely related to the transit trade industry. In order to decide upon the industries that can be plausibly associated with "transit trade," we identify industries that include, in their SIC code description, the word "freight," as this word refers to goods transported in bulk by truck, train, ship, or aircraft. In total, five sectors were selected. These, shown in Table 3 below, include both the transport of passengers and freight, thus the use of these codes may thus result in in an over-estimate of the number of individuals employed in the transit industry.

Table 3. SIC codes and descriptions for transit trade (3-digit level)

SIC code	Sub-sector
711	Railway transport
712	Other land transport
721	Sea and coastal transport
722	Inland water transport
730	Air transport

Source: Authors' estimation.

A better estimation may be obtained by limiting the relevant SIC codes to those that only involve the transportation of goods. However, we can only identify two such codes (shown in Table 4), and these are both at the 4-digit level, which may not be available in the relevant survey data. Furthermore, only using these two codes would likely result in an under-estimation as freight transport can only be isolated for road travel and not other means of transport.

Table 4. SIC codes and descriptions for transit trade (4-digit level)

SIC code	Sub-sector
7123	Freight transport by road
7419	Other transport activities

Source: Authors' estimation.

We thus recommend that the 3-digit level codes be used. From a skills perspective, an over-estimate is unlikely to be a problem for the method given that the overestimate will include all the relevant occupations for the transit trade industry (and given that the occupations that will be included for passenger transport in the overestimation will be very closely related to those required for freight transport in any case). Unfortunately, being unable to isolate freight from passenger transport may, however, result in an overestimate of the current size and potential of the transit trade sector. This complication will have to borne in mind in the application of the method to this sector in particular.

2.2.4 Tourism

Tourism can be defined as the "activities of persons defined as visitors. A visitor is someone who is making a visit to a main destination outside his/her usual environment for less than a year for any main purpose [including] holidays, leisure, recreation, business, health, education or other purpose […]. This scope is much wider than the traditional perception of tourists, which included only those travelling for leisure," (UNWTO Statistics Guidelines, 2010).

Tourism is a seen as a vehicle for economic growth in many countries—especially developing countries—that rely on tourism to generate foreign currency. To gauge the growth potential of the sector, the economic contribution of tourism must be measured in a methodological way. As tourism is not defined as an industry in the standard SIC codes, the Tourism Satellite Account (TSA), which attempts to measure the size of the tourism sector, was created by the United Nations World Tourism Organization (UNWTO). The TSA does so by, first, identifying industries typically associated with the tourism sector, (e.g., accommodation, tourist attractions, leasing of modes of transport, restaurants, etc.), and then estimating the number of visitors in each of these industries, multiplied by the average spend of these visitors.

We can use the industries the UNWTO includes in the TSA for the purpose of identifying individuals employed in tourism-related occupations. It is, however, important to note that these industries identified below are at the 4-digit level, and may not be easily accessible in labor force data for some countries.

Table 5. SIC codes and descriptions for tourism (4-digit level)

SIC code	Sub-sector
4911	Passenger rail transport, interurban
4922	Other passenger land transport
5011	Sea and coastal passenger water transport
5021	Inland water transport
5110	Passenger air transport
5510	Short-term accommodation activities
5520	Camping grounds, recreational vehicle parks- and trailer parks
5610	Restaurants and mobile food service activities
5629	Other food activities
5630	Beverage serving activities
5590	Other accommodation
6810	Real estate activities with own or leased property
6820	Real estate activities on a fee or contract basis
7710	Renting and leasing of motor vehicles
7721	Renting and leasing of recreational and sports goods
7911	Travel agency activities
7912	Tour operator activities
7990	Other reservation service and related activities
9000	Creative, arts, and entertainment activities
9102	Museum activities and operation of historical sites
9103	Botanical and zoological gardens and nature reserves
9200	Gambling and betting activities
9311	Operation of sports facilities
9319	Other sports activities
9321	Activities of amusement parks and theme parks
9329	Other amusement and recreation activities, n.e.c.

Source: UNWTO (2010).

Another potential approach is to examine the tourism industry using an occupational lens, which requires identifying individuals employed in the tourism industry through the use of occupational codes rather than industry codes. In the context of identifying skills requirements, this could prove to be a useful exercise. In addition, occupational codes in labor force surveys are usually provided at the 4-digit level (as opposed to the 3-digit level of SIC codes), providing a greater level of granularity. According to the UNWTO, there are eight main occupations significantly related to tourism (Table 6):

Table 6. Occupation (ISCO 08) codes and descriptions for tourism (4-digit level)

Occupational code	Description
1225	Production and operations managers of hotels and restaurants
1315	General managers of hotels and restaurants
3414	Travel consultants and organizers
4221	Travel agency and related clerks
5113	Travel guides
5122	Cooks
5123	Waiters, waitresses, and bartenders
8322	Car, taxi, and van drivers

Source: UNWTO (2010).

An obvious shortcoming of this approach is that not all who are classified in the occupations described above will necessarily be linked to the tourism industry. However, combining the relevant occupational codes with the 26 industries associated with tourism (outlined earlier), creating a single, unified “tourism industry” with the associated occupations, might enable a more precise estimation of individuals employed within the tourism sector.

3. Employment creation potential

We start here with a discussion of two ways in which to view the employment creation potential question. First, we consider indicators of labor intensity, which inform us about employment creation potential in any particular sector on the assumption of constant labor intensity over time and varied assumptions about national and sectoral growth. We then also consider how the unlocking of opportunities and addressing of constraints within the context of a global value chain analysis for any particular sector can provide insights on the employment creation potential of the sector. We conclude this section by considering how the estimates of potential employment obtained through these methods can be used to obtain occupational requirement profiles for the sector in line with the estimates of the sector's potential employment.

3.1 Indicators of labor intensity

3.1.1 Labor-capital and labor-to-value added ratios

One of the important factors influencing the employment creation potential within an economy concerns how intensively labor is used in the production process. These measures of labor intensity are fundamental to the estimation techniques discussed later in this section and, as a result, they are a reasonable place to begin the discussion on potential employment.

To begin, one needs an $n \times 1$ vector of employment per industry, P, where element p_i is the number of employed individuals in industry i. In the case of this paper, one would identify the employment levels of the industries without smokestacks and include these as the various elements in P. Furthermore, one needs an $n \times 1$ vector of total output flow, X, where each element x_i is the total output for industry i.

Once this information has been obtained, these vectors need to be transformed into diagonal matrices, denoted as $DIAG(P)$ and $DIAG(X)$, respectively. These $n \times n$ matrices are made up of the elements p_i and x_i down the diagonal of $DIAG(P)$ and $DIAG(X)$, respectively, and all off-diagonal elements are equal to 0. Hereafter, one can calculate the labor-to-value added ratios for each of the sectors as follows:

$$N = DIAG(P)\big(DIAG(X)\big)^{-1}$$

The diagonal elements of the matrix N represent the labor-to-value added ratios for each sector of interest.

Tregenna (2015) utilized the method described above to estimate the labor-to-value added ratios for different subsectors in the manufacturing and services sectors of the South African economy. The data used for calculating these ratios were available from both the South African Standardised Industry Database (SASID) and a combination of the October Household Survey (OHS) and the Labor Force Survey (LFS). The extent to which this method can be applied to other African countries depends on the availability and quality of labor force data in these countries. In Section 4, we note some of our concerns in this regard.

An advantage associated with the labor-to-value added ratios method is that the employment vector can be divided up according to a number of demographics—for example, skill level, age bracket, or gender (Tregenna, 2015; Calí et al., 2016). This may be of particular use in the current context, where there is a particular focus on addressing youth employment in industries without smokestacks. By modelling the employment vector P as a vector of youth employment, one can narrow one's focus to measures of youth employment potential as opposed to general employment trends. (See Box 1 for more on Labor-to-value added ratios for South Africa.)

Box 1: Labor-to-value added ratios for South Africa

In the case of South Africa, one can make use of GDP information provided by Statistics South Africa, as well as the Quarterly Labour Force Survey (QLFS) in order to calculate labor-to-value added ratios. Using information for the fourth quarter of 2018, the values of these ratios were calculated for the nine main 1-digit SIC code industry classifications and are presented in Table 7:

Table 7. Labor-to Value Added Ratios for South Africa, Q42018

Sector	Labor-to-value added ratio
Agriculture; hunting; forestry and fish	11.68
Mining and quarrying	1.93
Manufacturing	4.54
Electricity; gas and water supply	2.02
Construction	13.89
Wholesale and retail trade	7.80
Transport; storage and communication	3.52
Financial; insurance; real estate and business services	4.10
Community; social and personal services	21.43

Source: Author's calculations from Statistics South Africa (2019a, 2019b).
Note: GDP values used to calculate labor-to-value added ratios expressed in millions of 2010 rand.

These labor-to-value added ratios can be interpreted as the number of individual workers required per sector to increase GDP in that sector by R1 million (in 2010 prices).[1] Thus, lower values of the labor-to-value added ratio are indicative of sectors where workers add more to GDP on average. The lowest ratios are found in the mining and quarrying sector, as well as the electricity gas and water supply sectors, followed by transport, storage and communication, financial services, and manufacturing. This result is potentially indicative of an abundance of capital in these sectors, as marginal product of labor is high. However, it does not necessarily say much about the potential employment in such sectors: Although there may be a relative labor shortage, these sectors may be highly mechanized, and, as a result, may not have the scope to increase employment levels given skill-based labor supply shortages.

The calculation of labor-to-value added ratios is relatively simple and is not particularly data-intensive, requiring only employment and output data. However, a key drawback is that these measures do not truly model potential employment on their own. It would be necessary to have predictions of the output produced by each of the industries without smokestacks before one can make use of the labor-to-value added ratios to model potential employment. As a result, while these ratios are simple to calculate, their power in predicting future employment trends is limited in scope.

3.1.2 Employment elasticities

Modelling employment growth potential through the use of employment elasticities has been a popular choice among researchers, whether modelling the impact of increased own-sectoral growth, as done by Fox et al. (2013), or whether measuring the impact of growth in employment of other sectors, as outlined by Moretti (2010), and implemented by van Dijk (2017) for the United States, and Wang and Chanda (2018) for China.

The estimation of employment elasticities can be relatively simple, only requiring a time series of employment data per sector and the GDP contribution by sector. This is the method favored by Fox et al. (2013) in their investigation of employment elasticities for sub-Saharan African countries, which required running a linear regression of the form

$$\Delta \ln(E_{it}) = \alpha \Delta \ln(GDP_{it}) + \varepsilon_{it} \ldots (1)$$

where E_{it} is the sectoral employment level in country i in period t, and GDP_{it} is the sectoral contribution to the GDP of country i in period t. Separate regressions for each sector are run in order to capture the effect of growth in individual sectors on their employment levels. The employment elasticity, α, can then allow one to determine how a given sector's employment can grow in the future, given a particular GDP growth trajectory.

As was the case with the labor-to-value added ratios, the data needed for estimation of employment elasticities is relatively easy to come by, and, as a result, should not prove to be a challenge in this method of estimating potential employment. However, there are other shortcomings in the econometric method that indicate that this method of estimating employment elasticities can be unreliable. For example, there is often higher volatility in GDP growth than in employment growth, leading to unreliable estimates of employment elasticity (Fox et al., 2013). In order to combat these problems, it is necessary to ensure that the time series over which the regressions are run is long, or that one adopts panel data techniques to counter the persistence of employment over time (Fox et al., 2013).

Van Dijk (2017) further points out potential endogeneity problems when estimating employment elasticities and suggests the use of instrumental variables and two-stage least squares to circumvent these issues. However, there is little consensus as to what a good instrument would be in this case, which could be a potential challenge in running more sophisticated econometric specifications.

Even though there are methodological problems with the estimation of employment elasticities, Fox et al. (2013) find that their employment elasticities do well in predicting sub-Saharan African employment levels. The estimates based on 2004/2005 data were found to be robust in predicting 2010 employment levels for a subset of African countries, leading to the conclusion that simple employment elasticities perform relatively well in modelling employment growth. Thus, if one could obtain an estimate of potential GDP growth in each industry without smokestacks, one may be able to obtain relatively simple, but rather robust, estimates of potential employment for each industry in question.

Once again, this method of estimating employment elasticities is easily extended to apply to youth employment and can be disaggregated by gender. By simply restricting the employment variable to only capture youth employment, one can calculate youth employment elasticities for each sector. Hereafter, the elasticities can be used as before to determine the effects of sectoral output growth in the industries without smokestacks on youth employment.

Subject to data availability, one could also adopt a less parsimonious specification of the regression function, as has been done by van Dijk (2017) and Wang and Chanda (2018) in estimating city-specific employment elasticities. The prevailing method in these papers is based on that of Moretti (2010), who estimates cross-sectoral employment elasticities, particularly focusing on how changes in employment in the tradeable goods sector translate to changes in employment in the non-tradeable goods sector. This method requires the addition of geographic characteristics as regressors to the right-hand-side of equation (1) above.

Box 2: Employment elasticity measures for sub-Saharan Africa

Fox et al. (2013) present a table of elasticity estimates produced by running their specified regression for various groupings of sub-Saharan African countries. South Africa was included separately as it has performed poorly employment-wise in recent history and, as such, warranted its own estimates.

The estimation procedure was run across a number of different income groupings, which were constructed by considering whether a country was resource-rich or not, coupled with the level of per capita income in the country (Fox et al., 2013). The results of this estimation procedure are shown in Table 8 below.

Table 8. Employment elasticity estimates for sub-Saharan Africa by income grouping

	Low income	Lower-middle income	Resource-rich	Upper-middle income (excluding SA)	South Africa
Agriculture				-0.8	-1.0
Wage industry	0.9	0.8	0.6	0.6	0.5
Non-wage industry	0.7	0.6	0.7	0.3	0.3
Wage services	0.8	0.8	0.8	0.7	0.5
Non-wage services	0.8	0.9	0.7	0.6	0.5

Source: Fox et al. (2013).

Interpretation of these parameters is simple enough: As an elasticity, one can interpret a 1 percent change in sectoral GDP as leading to the estimated value percentage change in employment in that sector. For example, one could interpret South Africa's wage industry elasticity as a 1 percent increase in the GDP of wage industries leading to a 0.5 percent increase in employment in wage industries. The majority of these elasticity estimates lie below 1 in absolute terms, indicating that employment is relatively inelastic to changes in GDP in sub-Saharan Africa, which represents a potentially poor trajectory for employment as countries continue to develop. These estimates allow one to determine what employment prospects are in a given industry, assuming a particular growth in GDP—and as a result provide a rough estimate of the potential employment available per sector, making them a useful tool to determine employment by sector in the future.

3.1.3 Employment multipliers

Yet another method of estimating potential employment is through the calculation of employment multipliers. There are two methods of calculating employment multipliers—the Input-Output approach adopted by Tregenna (2015) and Stilwell et al. (2000), as well as the regression approach adopted by van Dijk (2017).

3.1.3.1 The Input-Output approach

In the economics literature, the Input-Output (IO) model is widely used to measure potential employment. The main idea behind the IO model is that it estimates the magnitude of intra-industry linkages, both forward and backward (Ernst & Sarabia, 2015). As a result, employment multiplier effects can be estimated (Ernst & Sarabia, 2015). Troiano, Toledano, and Maenlling (2017) provide a step-by-step guide on how to implement this model, provided that an IO table can be found for a particular country.

In order to calculate employment multipliers using the Input-Output approach, it is necessary to have calculated the matrix of labor-to-value added ratios, N, as detailed in section 3.1.1. Furthermore, one requires access to an Input-Output (IO) table or a social accounting matrix (SAM) for the country in question, such as those made available through the Global Trade Analysis Project

(GTAP) database. In the case of South Africa, for example, these tables are published by Statistics South Africa, with the most recent data available for 2013 and 2014 for 50 different industries (Statistics South Africa, 2017). IO tables also exist for a number of other African countries, including (but not limited to) Botswana, Burkina Faso, Burundi, Ghana, Malawi, Senegal, Zambia, and Zimbabwe, through the Eora global supply chain database.[3]

A major challenge faced in the current research is being able to identify the industries without smokestacks among these pre-defined industries in the IO tables. If, for whatever reason, a particular industry without smokestacks is not defined in the IO tables or SAMs for a particular country, then this analysis will no longer be viable for that industry.

Assuming the IO table has been obtained and manipulated to represent the industries of interest, the result should be a matrix where elements represent how much of a commodity produced by the (row) industry is needed as an intermediate input for the industry represented by the column (Statistics South Africa, 2017). This matrix is denoted as A, and is referred to generically as the input coefficient matrix, or the technical coefficient matrix.

One can use this matrix A to calculate the Leontief inverse matrix, $Z = (I - A)^{-1}$, where I represents the identity matrix of appropriate dimension. Once this inverse matrix has been calculated, one can construct a matrix of employment multipliers as follows:

$$M = NZ$$

where m_{ij} can be interpreted as the number of additional jobs in sector i that would be associated with one additional unit of demand in sector j.

Stilwell et al. (2000) made use of this Input-Output method of calculating employment multipliers to analyze the GDP multipliers for the South African economy, with a view to determining the relative importance of the mining sector in employment creation. They note that, while this calculation is possible in the South African case, the method does have some shortcomings, most notable of which is the fact that the IO approach does not account for resource depletion, which is a real challenge faced by the South African economy (Stilwell et al., 2000). Furthermore, Tregenna (2015) indicates that the method does not make any distinction between inputs sourced domestically and those sourced internationally, which can lead to the stimulatory effects of industries on employment being overstated. As a result, one should adjust for imported goods by obtaining an IO table that is netted of imported products.

Box 3 and Table 9 below present employment multipliers calculated for South Africa using the most recent available Input-Output data.

[3] The full list is available here: https://worldmrio.com/countrywise/

Box 3: Employment multipliers in South Africa

In order to estimate employment multipliers for South Africa, one needs to make use of the Input-Output tables as reported by Statistics South Africa (2017). A potential challenge is that the Input-Output tables are only available up to the end of 2014, meaning that any projections made on more recent employment data requires the assumption that the same Input-Output ratios must hold for more recent years. It is likely that data for other African countries will also not be for the latest year.

For the purposes of computational convenience, this is assumed in this case, as the calculation of employment multipliers is based on the labor-to-value added ratios presented in Box 1 of this section. Once again, the analysis in this example is illustrative of the nine major 1-digit SIC codes in South Africa, and. as a result, the Input-Output table must be condensed from a 50-industry matrix to a 9-industry one. This conversion is relatively straightforward, as it simply requires aggregating more granularly defined industries into their respective 1-digit counterparts.

Following the method outlined above, one can calculate the employment multipliers for South Africa, which are presented in Table 9. The elements m_{ij} of this matrix are interpreted as the number of additional jobs that could be created in sector i if there were to be a unit increase in demand in sector j. In this case, numbers are interpreted relative to a R1 million increase in demand in a particular sector.

Own-industry employment multipliers for sectors such as community services and construction are particularly high, at 23.85 and 14.11, respectively. This potentially indicates that these industries are most able to create employment should they be subject to an increase in demand. Values across the rows for community services are also mostly above 1, indicating that, should demand for these services increase, they are likely to have spillover effects and create multiple jobs in other industries as well. This result is similar for the manufacturing sector.

It should, however, be noted that these values calculated are not net of imports and, as such, may well overstate the employment creation potential of the South African economy.

Table 9. Projected employment multipliers for South African sectors, 2018

	Agriculture	Mining	Manufacturing	Electricity; gas and water	Construction	Wholesale trade	Transport & storage	Financial services	Community services
Agriculture	12.35	0.26	1.16	0.17	0.49	0.25	0.28	0.16	0.22
Mining	0.17	2.06	0.40	0.35	0.23	0.09	0.10	0.06	0.08
Manufacturing	2.67	1.75	7.90	1.15	3.29	1.63	1.88	1.07	1.23
Electricity; gas and water	0.11	0.18	0.14	2.40	0.07	0.07	0.06	0.07	0.04
Construction	0.05	0.06	0.07	0.03	14.11	0.04	0.11	0.08	0.04
Wholesale trade	1.21	0.72	1.48	0.50	0.72	8.65	0.93	0.59	0.57
Transport & storage	0.61	0.59	0.53	0.28	0.47	0.48	3.95	0.34	0.31
Financial services	0.75	0.64	0.79	0.45	0.92	1.18	1.10	5.80	0.76
Community services	2.26	1.63	3.05	0.82	1.80	1.26	2.07	2.45	23.85

Source: Author’s calculations from Statistics South Africa (2017, 2019a).

Note: Values are interpreted as the number of jobs that would be created in the row industry due to a R1 million increase in demand for the column industry.

3.1.3.2 The regression approach

A second approach to calculating employment multipliers relies on regression-based techniques, as adopted by van Dijk (2017) and Wang and Chanda (2018). There are two different regression-based approaches to estimating employment multipliers, one of which requires estimating an employment elasticity first, and the second, which simply estimates the employment multiplier directly.

The first of these methods requires the estimation of an employment elasticity to begin with. Van Dijk (2017) estimates this elasticity in the context of city-specific inter-industry elasticities, however, by logical extension, one should be able to adapt this method to own-sector elasticities. The equation estimated by van Dijk (2017) is as follows:

$$\Delta Jobs^{i}_{c,t+1} = \alpha + \beta \Delta Jobs^{j}_{c,t+1} + \gamma X_{c,t} + \delta Time_t + \varepsilon_{c,t}$$

where $\Delta Jobs^{i}_{c,t+1}$ measures the percentage change in employment in city *c* between time *t* and time *t +1* in sector *i*, $\Delta Jobs^{j}_{c,t+1}$ measures the percentage change in employment in city *c* between time *t* and time *t + 1* in sector *j*, $X_{c,t}$ is a vector of characteristics specific to city *c*, $Time_t$ is a dummy variable which controls for national shocks in employment, and $\varepsilon_{c,t}$ is the error term.

Given that the $\Delta Jobs^{k}_{c,t+1}$ variables are percentage changes, the parameter β is the employment elasticity that models how a change in employment in sector j feeds through to employment levels in sector i. A logical extension would allow for sector j to simply model the entire country and, as such, one can determine how changes in total employment may affect a specific industry.

Once this employment elasticity has been estimated, one simply needs to scale it by the relative size of sector j to sector i in order to obtain the employment multiplier. A drawback to this particular method, however, is that the employment elasticity estimated has to remain constant across all sizes of the industry, an assumption that is arguably unrealistic (van Dijk, 2017).

The second regression-based method to estimating employment elasticities requires simply redefining the $\Delta Jobs^{k}_{c,t+1}$ as the relative contribution of the sector to overall employment (van Dijk, 2017; Wang & Chanda, 2018). In other words:

$$\Delta Jobs^{k}_{c,t+1} = \frac{E^{k}_{c,t+1} - E^{k}_{c,t}}{\Sigma_m E^{m}_{c,t}}$$

where $\Delta Jobs^{k}_{c,t+1}$ is the change in employment in sector *k* in city *c* at time *t + 1*, $E^{k}_{c,t+1}$ is employment in sector *k* at time *t + 1*, $E^{k}_{c,t}$ is employment in sector *k* in city *c* at time *t*, and $\Sigma_m E^{m}_{c,t}$ is the sum of employment across all sectors *m* in city *c* at time *t*.

In this case, the parameter β is directly interpretable as the employment multiplier. An advantage of applying this second method of estimating the employment multiplier is the fact that one need not assume the employment elasticity of a particular sector as constant across all sizes of the sector. Furthermore, one would be able to directly estimate the effects on youth employment by simply limiting the measure of employment in each sector to only measure youth employment. The multiplier effects can also be measured by gender.

While these regression-based techniques are relatively straightforward to implement, the challenge faced in this case is the potential endogeneity of the levels of employment in the two sectors of interest (Moretti, 2010; van Dijk, 2017; Wang & Chanda, 2018). As a result, the only method for consistently estimating the employment multiplier requires instrumental variable regressions. While certain instruments have been suggested, the use of instrumental variable regressions is widely open to criticism due to the difficulty of finding an appropriate instrument.

Box 4: Inter-sector employment multipliers in China

In their paper on the city-level employment multipliers present in the Chinese economy, Wang and Chanda (2018) present results for the impact of increases in manufacturing employment on the number of jobs in the non-tradeable sector of the economy. They presented three model specifications, which included different city-level control variables, and ran each specification using OLS methods, followed by the instrumental variable specification. The instrument of choice in this paper was the growth rate of manufacturing in each city, normalized by the relative size of the manufacturing sector in the city (Wang & Chanda, 2018). A summary of the estimation results can be found in Table 10 below.

Table 10. Estimates for employment multipliers between Chinese manufacturing and non-tradeable sectors

	OLS	IV
Model 1 (baseline)	0.499***	0.451***
	(0.052)	(0.078)
Model 2 (controlling for share of non-tradeable employment)	0.445***	0.287**
	(0.065)	(0.132)
Model 3 (controlling for share of government employment)	0.470***	0.339**
	(0.064)	(0.136)

Source: Wang and Chanda (2018).

The OLS estimates provided in Table 10 indicate that for every one additional job created in the manufacturing sector, there are between 0.45 and 0.5 jobs created in the non-tradeable sector. The instrumental variable regression results consistently report lower estimates for the inter-sector employment multiplier, but the results remain significant and below 0.5 for all models, indicating that the throughput of jobs from manufacturing to non-tradeable goods is relatively low.

Although this method of estimating employment multipliers is specifically applied to the inter-sectoral context within cities, a similar method could be applied to estimate the general employment multiplier for an "industry without smokestacks"—by simply replacing the dependent variable with the employment in the industry of interest, and the independent covariates with overall employment levels, or GDP growth rates of the industry.

3.1.4 Export job contents

The World Bank has recently released a database of Labor Contents in Exports (LACEX), which covers 120 countries for between 11 and 57 different sectors. The creation of these values is discussed by Calí et al. (2016), but closely mirrors the creation of the labor-to-value added ratios as discussed before. The main difference is that, instead of a vector of total output flow, one uses a vector of compensation of employees' shares of output (Calí et al., 2016). This database combines several different IO tables, SAMs, and exports databases to provide a tool that can be used to describe the extent to which exports support jobs and wages within the economy as a whole, as well as in specific sectors over time.

A disadvantage of the data as it is currently available is that it does not allow for one to predict the effects of policies or shocks which aim to move the equilibrium level of employment (Calí et al., 2016). The estimates are currently provided as equilibrium values of the labor content of exports, which are not appropriate to use to model shocks to the economic system.

While this is a serious drawback, if one were to assume that there was no shock to the economy, one could use these LACEX values in a similar way to the labor-to-value added ratios, and estimate what potential job creation could occur in each sector of interest, provided one has a potential growth trajectory of exports over time on which to base one's estimates. Thus, while it is possible that there may be a use for the LACEX database, it seems that it is not best suited to the task of predicting potential employment across countries.

3.1.5 Limitations of using indicators of labor intensity to estimate potential employment

This section has discussed four different, albeit related, measures of estimating employment intensity, and potentially expanding these measures into employment potential projections. While the majority of these methods rely on readily available data, mostly found in labor force surveys or readily available online databases, they still fall short of actually predicting the potential employment of industries without smokestacks.

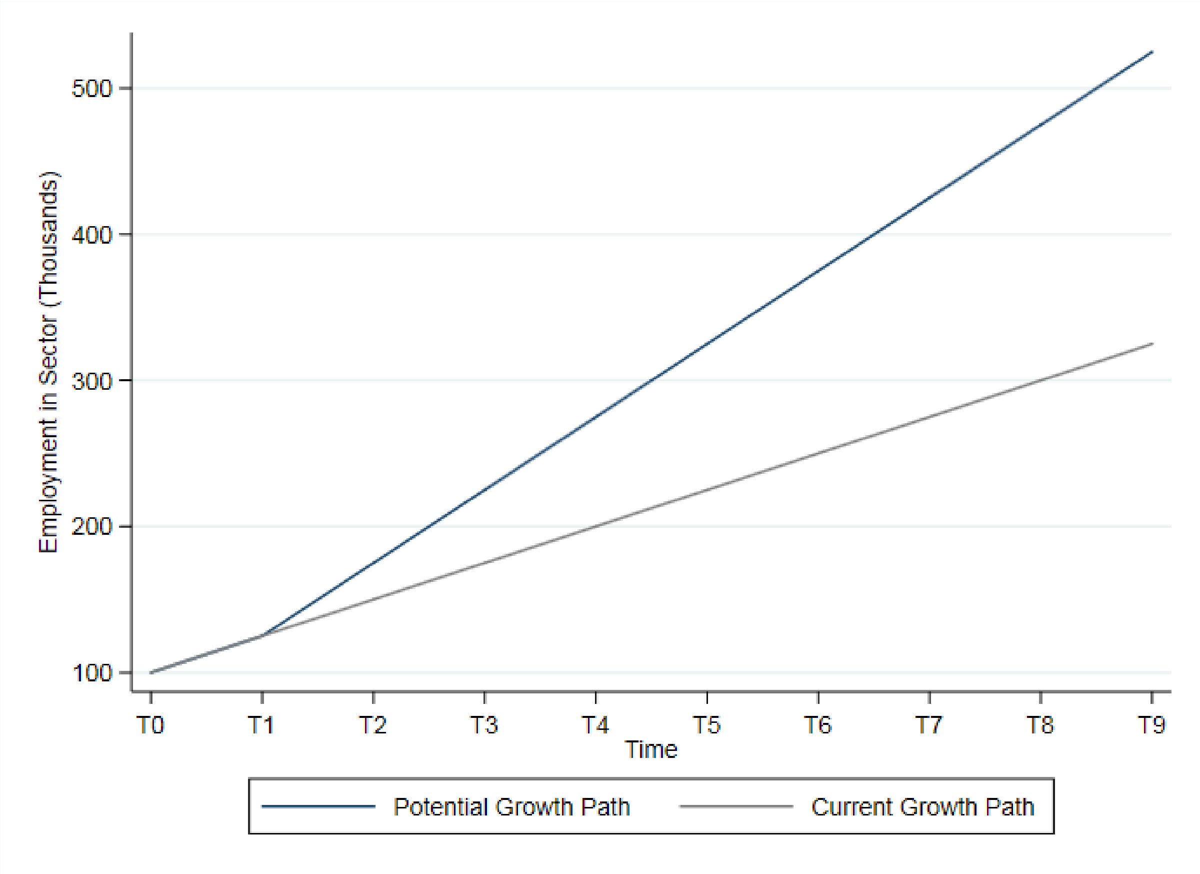
Indicators of labor intensity may be useful in the context of comparing sectors and their potential for employment growth among each other. However, even in this case, this assessment would be made assuming the measure of labor intensity remains constant, which, while maybe likely in some industries, may not be the case in other sectors where the sector is more dynamic and technological advances and globalization have a considerable impact on these measures over time.

One of the crucial shortcomings of all these measures is that, rather than providing employment forecasts that account for future technological and economic development, the majority simply calibrate estimates of future employment based on propagating existing historical trends in the data.

Projecting employment based on historical trends and current employment elasticities for a sector only tells us about employment on the current growth path. It does not tell us anything about the jobs that could be generated if changes are made in the sector to address constraints and unlock growth. To illustrate, Figure 5 provides a representation of employment in a sector over time based on two different growth paths. The first line, represented in grey, illustrates how employment might be expected to grow in a sector based on historical growth trends and a given employment elasticity. The blue line represents growth on a higher path in which either sectoral growth is higher, the employment elasticity of growth has increased, or both. In the figure, from T_0 until T_1, both paths are the same. However, if action is taken to unlock greater growth or increase the labor intensity of the sector (or both), the growth path can be elevated to the potential growth path at time T_1. This potential growth path represents a path in which opportunities for job creation are unlocked beyond what may be expected in the sector on the basis of available historical data. The gap between the two lines after T_1 represents the potential employment in the sector that can be unlocked over time if the growth path is elevated. If, however, the sector continues on the old growth path, these potential jobs are foregone. The increasing gap between the lines over time also indicates that the cost, in terms of employment, of remaining on the old growth path rather than elevating to a higher path becomes larger over time.

While being able to project employment trends may be useful, there is still a need to assess methods that investigate what the *potential* employment growth that elevates the sector to the higher potential growth path could be. This question is not adequately addressed by any of the above methods.

Figure 5. Potential versus projected employment growth in a sector



Source: Authors' illustration.

The method that seems to come the closest to estimating employment growth potential is that of employment elasticities. This method has held traction in the literature, but is somewhat plagued by econometric issues. It has also been shown to perform relatively well when actually attempting to use employment elasticities to predict employment in the future (Fox et al., 2013). Thus, it may be that, due to data limitations, one is forced to adopt one of the above methods. Should this be the case, employment elasticities seem to allow for the most flexible application of econometric techniques, easy modification to focus on youth employment, the potential to disaggregate findings by gender, as well as the ability to accommodate the industries without smokestacks. Where IO tables may provide a measure of intermediate interdependencies of industries, these are unlikely to define the industries without smokestacks of interest to this paper, for example, tourism.

Similarly, should any of the other indicators of labor intensity be used, an assumption needs to be made about growth or investment in the sector, and a number of potential jobs to be created in the sector can be estimated on the basis of this assumption. However, all of these projections of employment suffer from two key drawbacks: First, they can project a total number of jobs in the future based on current labor intensity and assumptions about growth on the current sectoral growth path. However, they cannot tell us about employment potential that can be unlocked through addressing constraints to growth and the sector being elevated to a higher growth path. Second, the type of estimates or projections that we would obtain using any of these indicators of labor intensity would not tell us anything about the type of jobs projected to be created; hence, we would not be able to use this total estimated number of jobs to ascertain the skills content and requirements of those jobs. With respect to the second drawback, we could potentially use the current breakdown of skills in the sector and assume that the new jobs created would be distributed in the same way: However, this assumption suggests that any growth in the industry basically replicates the current activities already being done in the industry being scaled up in line with the projected growth. Of course, this is a very strong assumption to make and does not take into account that growth in the sector could be distributed across activities and jobs in a manner that is different to the current distribution of the sector.[4] A particular drawback of this assumption is that it ignores changes in employment distribution that result from technological development over time. Given the onset of the Fourth Industrial Revolution and the speed with which technology is developing in the current world, a method that ignores technological advancement may critically misrepresent the development of the labor market in the future.

We thus identify a need to be able to consider potential for employment in a sector in a more nuanced manner that will enable us to allow for an estimate of potential employment that is not restricted to the current growth path and labor intensity of the sector; and secondly, allows for an estimate of not only a total number of jobs that a sector has the potential to generate, but also an indication of the type of the jobs that a sector has the potential to generate. We explore this approach, which acts as an alternative method to those proposed above, in the next section.

3.2 Employment creation potential within the context of sectoral and global value chains

3.2.1 Jobs within the context of global value chains

A value chain includes all activities required to produce a good or service, from conception to the stages of production (provision of raw materials, input of various components, subassembly, producer services, and assembly of goods) to delivery to consumers and, finally, to disposal after use (Farole et al., 2018). Global value chains (GVCs) include all the stages (or "tasks") of production increasingly taking place across a number of different countries. Inputs and semi-finished products and services are imported. Value is then added domestically, and the product is again exported for further processing or consumption. More than 70 percent of world services imports are now immediate services, while more than half of the world's manufacturing imports are now intermediate goods, illustrating the importance of GVCs in the modern global economy (Farole et al., 2018).

GVCs have the potential for at least three positive effects for developing economies (World Bank, 2017): The first is integration into the global economy more rapidly than ever before, by allowing them to use their comparative advantage to concentrate on a specific production task (Kowalski et al., 2015). The second is job creation through opportunities for participation in GVCs (UNCTAD, 2013). The World Bank (2017) notes the examples of jobs being created through iPhone assembly in China, call center operations in the Philippines, and automobile and auto parts production in Mexico and Thailand. The third is the opportunity for technology transfers or spillovers from developed countries to developed countries through local learning (Pietrobelli & Rabellotti, 2010; Kawakami & Sturgeon, 2012).

It is the second benefit in which we are explicitly interested, in the context of estimating potential employment for individual sectors in developing countries. However, the other two benefits also feed into the possibilities for job creation through GVCs.

[4] In Section 3.3, we explore how this drawback can be dealt with if the second (preferred but possibly not feasible) approach to estimate potential employment cannot be used.

Specifically, jobs are created through GVCs through movement along the value chain, known within the GVC framework as economic upgrading. Four types of upgrading with implications for employment are identified in the GVC literature, each of which requires differing levels of changes and firm learning (Gereffi & Fernandez-Stark, 2011):

(i) Process upgrading, which transforms inputs into outputs more efficiently by reorganizing the production system or introducing superior technology;
(ii) Product upgrading, or moving into more sophisticated product lines;
(iii) Functional upgrading, which entails acquiring new functions (or abandoning existing functions) to increase the overall skill content of the activities; and
(iv) Chain or inter-sectoral upgrading, where firms move into new but often related industries (Humphrey & Schmitz, 2002).

Corresponding with the opportunities GVC-oriented trade offers for developing countries to benefit from global integration, the nature of such value chains also presents substantial barriers to firms that lack the technology, skills, assets, and networks to take advantage of these opportunities. Identifying employment potential in GVCs should thus be viewed as the first part of a larger process. This first stage involves identifying opportunities for growth and job creation, thereafter planning (and ultimately implementation) for the requisite knowledge, skills, and asset attainment to achieve the growth opportunities is required. In our framework, the focus will be on using the value chain-based analysis to obtain insights with respect to the skills required by youth, so that the growth and jobs can materialize.

Through a detailed understanding of the industry's activities, how they relate to each other, and how these can be further integrated into the global economy through GVCs, potential for industry (and the corresponding employment) growth can be mapped out. Furthermore, through understanding the exact nature of this potential employment, the skills requirements for the sector can be understood and, ultimately, skill gaps for a country's population can be identified.

Here we consider a structured method for making this assessment within the context of global value chain integration. We note upfront, though, that the approach requires significant time and financial resources, and may not be best placed to assist in determining employment potential for any sector should these not be available. However, components of the method may be used as appropriate given any limitations in this regard.

3.2.2 A survey-based global value chain-focused method for estimating employment creation potential

The World Bank has published a Jobs In Value Chains Survey Toolkit[5] that indicates how value chain studies can be used to provide an "in-depth understanding of the interrelationships among firms that operate in a supply network and of the factors that determine the structure, dynamism, and competitiveness of these chains." This toolkit is part of a wider literature on global value chain analysis, but goes further than other work and is most relevant for the purposes of assessing employment potential. The approach aims to provide insights on the number of jobs, where they are located within value chains, and the extent and nature of relationships among actors in a value chain.

The approach involves value chain mapping and the use of firm-level surveys that quantify **potential employment.** The approach can help to identify constraints to business operations and growth. We outline the method and what it entails at a high level here. The guide has a strong

[5] Farole, T., Puerta, M., Canut, A. and Rizvi, A. 2018. Jobs in Value Chains Survey Toolkit. World Bank, Washington, DC.

focus on implementation methodology and can be consulted should the approach be deemed feasible and if specific guidance is required upon implementation.

There are five key components of the assessment:
(a) Background research (including value chain screening and initial mapping);
(b) Value chain mapping;
(c) Structured surveys;
(d) Semi-structured interviews and focus groups; and
(e) The analysis of the collated research and data

We briefly explain what each stage entails here, before relating the process to the specific question of determining employment potential for the purpose of identifying skill gaps.

1. Background research: Identifying activities with broad potential in the current sectoral value chain

This stage mainly requires desktop research in order to identify value chains that would be feasible to study under the time and financial constraints present. These value chains should be strategically identified according to their employment potential and their opportunities for integration into global value chains.

2. Value chain mapping: Understanding the value chain(s) identified for growth

A value chain map illustrates the actors that bring the product from its basic raw materials through to final consumption. A full mapping of all critical components of the specified value chain(s) should be undertaken through the use of available sample frames, existing research, and other information.

The first step in value chain mapping is to map all basic functions in the chain. The local value chain will likely not be available, and so the starting point would be a generic value chain map for the product or service being considered, which would then be adjusted to reflect the value chain in the specific country. The chain should record all individual activities in which value is added from end products back to the point of the basic inputs.

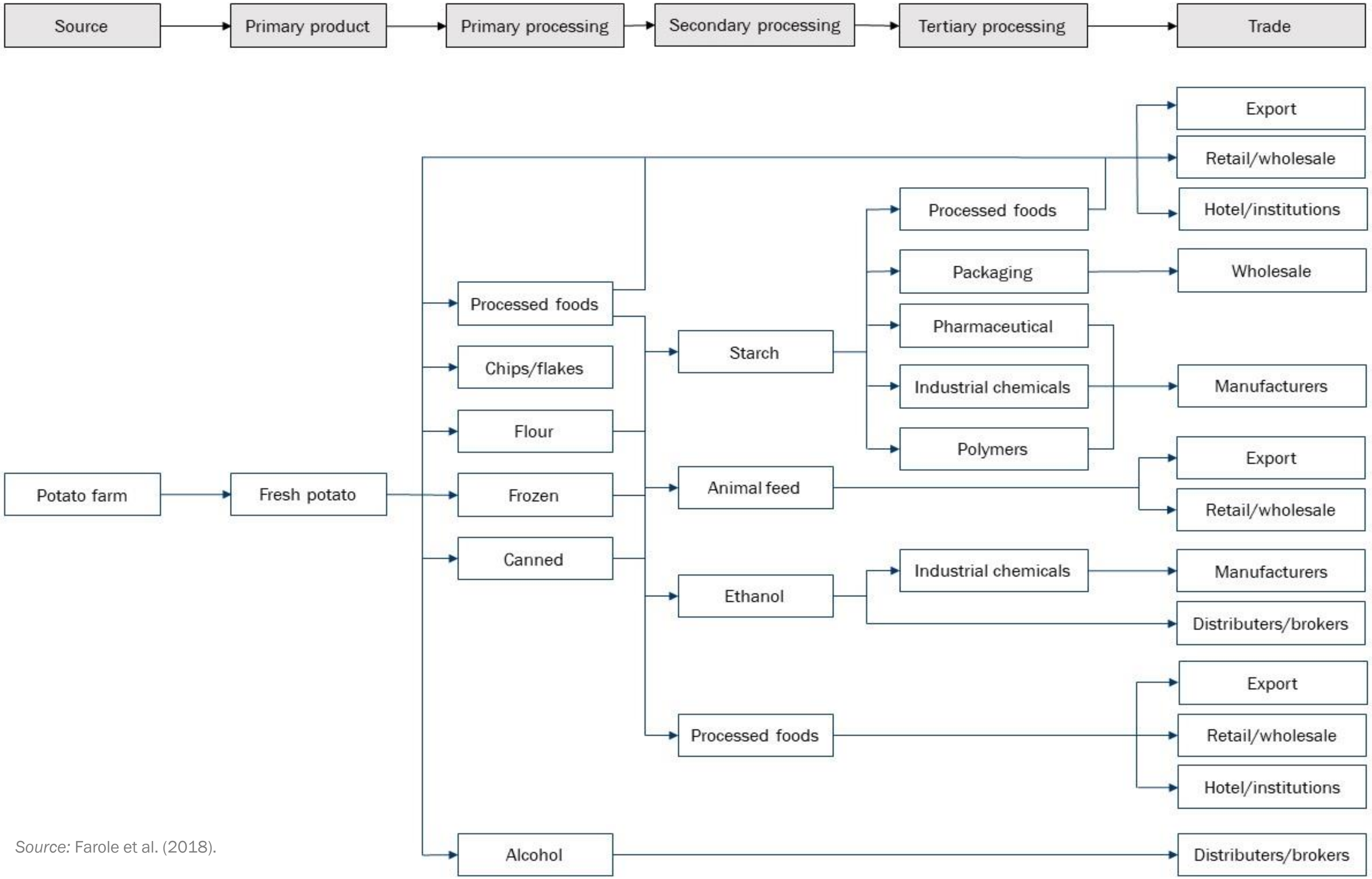
Figure 6 presents an example of a generic value chain for potato-derived products, adapted from Farole et al.'s (2018) pilot case study of the potato sector in Lebanon.

Once the broader product and value chain is established, the next step is to identify the relevant players or stakeholders for each node of the value chain. The specific names of key actors and number of firms at each stage should be estimated. Firms can also be distinguished on the basis of formality, size, and ownership (domestic or foreign), if these factors are relevant for the question being considered.

Because this step will guide the sample structure of the firms to be interviewed, the mapping must be as comprehensive, accurate, and up-to-date as possible. Another important aspect of this stage is identifying the critical nodes that will be selected for the quantitative interviews and any additional nodes to be covered by the qualitative approach.

Potential data sources for development of value chains include: previous value chain and sector chains; national and sectoral statistics; industry associations; and consultations with stakeholders. Social accounting matrices (SAM) and Input-Output tables (discussed as part of the potential employment estimate section) may also provide valuable information. These datasets provide information on transaction patterns—specifically inputs into sectors (from other sectors) and outputs from each sector into the others, which can identify links between sectors.

Figure 6. Example of a generic value chain: Potatoes



Source: Farole et al. (2018).

To limit fieldwork, secondary research should be used to provide relevant information relating to the value chain. Secondary research can also inform the interviews and enable the interviews and surveys to be more efficient with better attention paid to the key issues and stakeholders. These secondary data sources include existing value chain studies and enterprise surveys. Consultations with stakeholders, however, will deliver the most detailed and appropriate information, enabling an in-depth understanding of the structure of the industry, key activities, and key players in the industry, as well as the nature of the interactions within the industry value chain. At the very least, a value chain mapped on the basis of secondary data sources should be confirmed with preliminary field consultation before the survey stage commences.

3. Structured surveys

This is typically the most time and resource-heavy component of the process. The quantitative survey here should be specific to the sector in order to obtain specific sector and country insights. It should broadly seek to understand (i) the precise nature of the potential for job creation in the identified value chain(s); and (ii) the number and type of jobs that would be created should the potential be realized. Included in job type is an indication of the kinds of "soft skills" required to perform a given role. Examples include leadership ability, communication skills, and problem-solving skills.

4. Semi-structured interviews and focus groups

During this stage, qualitative methods are used to capture country and environment specific factors, record comments from key stakeholders, and note unique trends within the sector. The interview and focus group sessions not only gather information, they also engage key stakeholders in the wider value chain development process.

5. Analysis and results

In this phase, the results of the research and fieldwork are analyzed. The results should detail the structure and dynamics of the value chains, assess job creation opportunities and wider value chain competitiveness, and detail the main obstacles to growth. If appropriate, the report should also outline proposed interventions and a potential program of support to value chain competitiveness and job creation.

Within the results and across this entire process, for the purpose of identifying sectoral employment potential and ultimately skill gaps for the youth, the following four things in particular should be uncovered:

(i) An understanding of the industry's current value chains and extent of integration into global value chains
(ii) Products or services and value chains in the sector with potential for unlocking integration and growth
(iii) Specifically, an understanding of where scope exists in the sector's value chain(s) for:
   a. New activities to be introduced into the value chain
   b. Where current activities in the value chain can be upgraded
   (collectively a and b can be termed as "value chain job creation scenarios")
(iv) For each new activity to be introduced and each segment of the value chain to be upgraded:
   a. An estimate of the number of jobs to be created
   b. The type of jobs to be created (and number of each type of job to be created)

Box 5: Estimating potential jobs in a GVC framework

Having identified a specific product or service value chain with potential for GVC integration and growth that currently exists in the sector in the country, one then takes the following steps to identify the number of potential new jobs that can be created in the value chain:

Step 1. Map value chain for the identified product or service. This mapping should be at a level that illustrates each activity undertaken in the chain, and the number and type of jobs supported at each activity node.

Step 2. Estimate the current number and type of jobs supported at each activity node.

Step 3. Identify where and how current activities in the value chain can be upgraded. Each of these can be termed an "upgrading (or job creation) scenario." More than one may be applicable to a particular value chain. There may also be different alternative upgrading scenarios of which not more than one can actually be applied. A choice will have to be made as to which scenario is most relevant in this case, for the purpose of the final estimation.

Step 4. Estimate the number and type of jobs that will exist should upgrading take place successfully. This estimation will be used to update the current occupational profile of the sector.

These steps can be represented as inputs into the value chain jobs estimation tables below.

Table 11. Example of a value chain job estimation table (number of jobs only)

VC Activities	Total jobs in current VC	Upgrading 1	Upgrading 2	Total jobs in upgraded VC
Activity 1				
Activity 2				
Activity 3				
Activity 4				
Total				

Source: Farole et al. (2018).

Table 12. Example of a value chain job estimation table (number and type of job)

VC Activities	Jobs by type in current VC	Jobs by type in Upgrading 1	Jobs by type in Upgrading 2	Total jobs by type in upgraded VC
Activity 1				
Occupation 1				
Occupation 2 etc.				
Activity 2				
Occupation 1				
Occupation 2 etc.				
Activity 3				
Occupation 1				
Activity 4				
Occupation 1				
Total				

Source: Own adaptation from Farole et al. (2018).

Table 11 notes only the number of total jobs. However, Table 12 is more relevant for our purposes as it lists, for each activity, the number of individuals employed in specific occupations. Should the survey responses used to construct these estimates not be robust enough to provide precise numbers of people to be employed in specific occupations in the upgraded scenario, a list of occupations will suffice. A list alone will, however, only allow for the identification of occupational skill gaps and not a sectoral skill gap.

Box 6: Example of a value chain employment potential estimation: Poultry in Zambia

Farole et al. (2018) provide an example of how the jobs estimation method has been applied with specific reference to the poultry sector in Zambia. We note here key results of various components of the method.

Identification of value chain: Poultry was identified as a value chain of interest on the basis of its growth potential, strong links to domestic inputs, the fact that it accounts for near half of the livestock subsector in Zambia, and that women are well targeted within the sector.

Identification of key activities in value chain: The appropriate activity nodes were identified as: Day old chicks, feeding, rearing, processing, and distribution.

Estimate of current jobs in value chain: For each of these activities the numbers employed in both the traditional and modern sectors were estimated, as noted in Table 14 below.

Upgrading/job creation scenarios: Only one subsector of the overall poultry value chain was identified for growth and/or upgrading. The identified opportunity for upgrading the sector was growing and further modernising the broiler subsector on the basis of its labor intensity. The broiler component of the VC currently provides 32 000 jobs (26 000 in the traditional model and 6 000 in the modern model). Two possible scenarios are considered:

a. Increased demand is captured by both the traditional and modern sectors, maintaining the current market shares of the two sectors
b. Increased demand is captured by the modern sector only.

Both scenarios assume population growth of 3.1 percent per annum and a 25 percent increase in consumption of broilers.

Job estimation in case of upgrading/unlocked growth: Using data related to the profile of the workforce along with the value chain analysis, the results revealed the following:

In scenario A, there is potential to create an additional 17 000 jobs by 2022.

In scenario B, there is potential to create an additional 9 000 jobs by 2022. This is fewer than scenario A, but these jobs are likely to be better quality jobs.

The results can be summarized and represented as in the Job Estimation table below:

Table 13. Example of a job estimation for the poultry value chain in Zambia.

	Total jobs in current VC		Value chain job creation scenarios			
			Scenario A		Scenario B	
	Traditional	Modern	Traditional	Modern	Traditional	Modern
Day-old Chicks	325	175	503	271	325	449
Feed	8,520	3,496	13,188	5,411	8,520	8,967
Rearing	15,061	1,689	23,304	2,614	15,016	4,333
Processing	0	210	0	326	0	540
Distribution	1,750	48	2,716	74	1,750	123
	25,611	5,618	39,711	8,696	25,611	14,411

Source: Farole et al. (2018)

This specific analysis focused on the number of jobs and not types of jobs. In the type of analysis we would need to undertake, we would need to take this analysis further and identify the precise types of jobs under each scenario. It is likely that the jobs under the modern scenario will be more highly skilled occupations, while the jobs potentially created under scenario B will be less skilled occupations. The skills implications will obviously differ depending on the appropriate scenario aimed for.

A disadvantage of this approach is that this type of information is very subjective. It is thus imperative that the survey sample and approach be carefully considered to be able to obtain reasonable estimates of these. An undertaking of such an exercise at the appropriate scale to obtain these estimates may be very costly in terms of both financial resources and time.

One advantage is that the approach can provide a good indication of where the industry can be expected to be in the future, as well as the types of occupations that will be necessary to have the skills for, to be able to achieve this potential. The key advantage is the insights the approach can yield with respect to not only the total sectoral employment potential, but the breakdown of that potential by types of jobs (or occupations). The micro-based approach allows a nuanced consideration of exactly where jobs can be expected to be generated in the sector, thereby allowing a detailed consideration of the types of skills required for those identified jobs and occupations.

However, being based on subjective feedback related to the sector's potential, the exact scope of the possibility of estimating the exact *number* of opportunities in the identified jobs is questionable. While we may reasonably expect survey participants and desktop research to tell us about the types of jobs for which we need to be able to access the skills, it is less clear that the approach would be able to forecast the exact number of individuals required in particular jobs (a requirement for us to estimate a precise skill gap).

What may be more reasonable is to expect survey participants to identify a list of jobs for which the industry will require skills at some point in time. This approach is limited in its ability to identify a skill gap as it does not directly compare available skills to skills that are currently required by an occupation. However, it is still useful for the purpose of identifying which skills need to be developed in order for youth to access future employment in a given sector. We explore this in more detail in the skill gap section below.

3.3 Using estimates of employment creation potential to obtain sectoral occupational profiles

The labor intensity measures noted above can be used to obtain an estimate of **total** potential employment for any specific sector quite easily. Given any measure of labor intensity, and for a given growth rate or investment (dependent on the measure), one can easily obtain an estimate of projected employment. This estimate will most likely, given the available data upon which to project employment, be an estimate of employment **on the current sectoral growth path**. That is, this will be an estimate of the potential employment that can be generated given a projection of growth or investment, based on historical trends and the current capital-labor ratios.

To obtain a measure of potential that takes into account that growth in the sector may exceed the projected level of growth should certain conditions be met, one can scale up the growth measure based on some criteria. However, this projection would still be based on current labor intensity measures, which are assumed to be constant. One could make assumptions about how these would need to change to improve employment potential as well. However, the basis for these types of assumptions would need to be carefully considered; and even given these assumptions, the estimate of potential employment that would be obtained would be an overall total employment figure.

Therefore, this approach even in the case of adapting growth rates and labor intensity measures to account for sectoral changes, will tell us nothing about the occupational makeup of the potential employment estimate.

To gauge the occupational makeup of the estimate, we will need to make certain assumptions about the total projected employment obtained through using measures of labor intensity. As a starting point, an occupational distribution of the current employment in the sector can be obtained from Labor Force Survey data. This data would give us estimates of the proportion of workers in the sector employed in different occupations (disaggregated as required).

We consider a number of scenarios for how the current distribution of occupations might look in the future. First, an extreme case is that the occupational distribution remains the same despite the growth in the sector. This scenario essentially assumes that the growth is distributed across activities and occupations in a manner that leaves the distribution unchanged. The projected total number of jobs in the sector could then be distributed according to the current occupational distribution of the sector. This scenario is unlikely, however. It is more realistic that some occupations in the sector will become more important over time, and others less important. Therefore, we need a method to determine how the number of jobs in different occupations will change over time. We suggest using a **trend analysis** of occupations in the sector over the time. That is, we consider how the occupational distribution has changed over time so that we can extrapolate that trend to obtain a distribution of the projected number of jobs in future.

A limitation, however, remains even in this case: The occupational profile will be based on past trends in sectoral occupational changes and not be truly representative of the potential of the sector, which could be locked. In other words, the occupational profile represents occupational changes on the current occupational distribution trend—but this trend could be different if opportunities for growth are unlocked, and the sectoral growth trajectory breaks with its previous trend.

This remaining limitation related to obtaining a future occupational profile of the sector can be avoided by using the survey-based GVC approach (or a similar survey-based approach). The survey-based approach has the advantage of explicitly taking into account the constraints to and opportunities for employment creation in a sector, rather than basing this estimate solely on current labor intensities and historical trends of sectoral growth. However, dependent on the type of survey feedback received, it may also be limited in its ability to tell us about the precise number of jobs of different occupations required to reach this potential.

The identification of employment potential within a value chain framework offers the advantage of providing a profile of the type of jobs that exist within the sector, as well as the type of jobs for which there is potential in the sector. This task is not possible in the case of the employment-intensity measures mentioned above, which consider sectoral jobs in a sector on an aggregate basis (and for which we offered an alternative). Being able to disaggregate potential employment based on job type may also assist with the identification of industry skills requirements, which is undertaken in the next section of the methodological framework.

An alternative approach to considering occupational requirements for a sector to reach its potential would be to use a comparator country as a basis for the sector's requirements. This approach would apply an *aspirational occupational distribution* to a projection of potential employment in the sector. In essence, the potential of the sector is taken to be that of the sector in a country in which the sector is already operating at a developed level. For example, one might think a reasonable aspiration for the tourism sector might be that of another developing or emerging country such as Mauritius. The occupational profile of this country would then be the potential occupational profile the country aspires to reach, and this occupational distribution can be applied to the projected employment. Potential is, however, very likely to be linked to the specific country's endowments and characteristics. It thus may be too idealistic to use any one country as an aspirational comparator. One could perhaps construct an index of countries most similar to the country in which the sector is considered to be well developed, and use the sector in these countries as the relevant comparator. In this case, it will be important to ensure that the countries chosen are similar to the country under consideration in terms of relevant indicators.

4. Labor skill requirements and identifying skill gaps

4.1 Skill imbalances and skill gaps: A definitional note

A hindrance to achieving sustained employment growth is the prevalence of a disconnect between the skills required by employers, and those skills possessed by the existing labor force. We have presented a number of methods for establishing the potential employment in a particular sector. However, for this potential to be achieved, workers must possess the skills that are required for the potential employment in the sector to be realized.[6]

A skill imbalance is when the skills that are required by a sector are not available to the sector, both in terms of those employed in the sector and in the wider labor force. "Skill imbalance" is a general term used in the skills literature to refer to issues related to skills needs in sectors and economies. Skill imbalances can, however, be made up of two different components. The first is *skill mismatches*, which occur when those currently employed in a given occupation have either inadequate skills to perform their duties or are over-skilled relative to their job requirements. Such mismatches can be measured through skills directly, or else through skill proxies such as qualification or field of study (Frogner, 2002; and OECD, 2017). In terms of qualification, the skill profile of workers in a given occupation is measured by education level and compared to the modal qualification required for a given occupation to determine the skill mismatch (OECD, 2017). Similarly, using field of study as a proxy for skill, the skill profile of those operating in a certain occupation is given as their field of study (Montt, 2015). The skill requirement for a specific occupation is assumed to be the field of study most fitting for that occupation. Calculating the share of workers that have jobs outside of their field of study is a measure of skill mismatch. These indicators have been used in the OECD Skills for Jobs Database to provide country-level scores for both qualification and field-of-study mismatch for OECD countries, as well as six developing countries, including South Africa (OECD, 2017). An extract of this output is shown in Table 14.

Table 14. Mismatches from OECD database by country, 2016

Main industry	Field-of-study mismatch	Qualification mismatch
South Africa	32.5	52.2
United Kingdom	38.0	41.0
European Union	32.8	33.5
OECD - Total	32.2	35.7

Source: OECD (2019).

While measuring skill mismatches is straightforward, as education and field of study are commonly included in labor force surveys, by their very nature, skill mismatches are limited to a firm's internal labor market, thereby excluding workers that are unemployed.

To better address the question we seek to address, the concept of skill gaps, often referred to as skill shortages/surpluses, is more appropriate. Skill gaps arise when employers cannot find suitably skilled workers from the external labor market to fill open positions (Frogner, 2002; and OECD, 2017). This can be the result of applicants being either under- or over-qualified. The concept of a skill gap is relevant here as the focus in this paper is on the under- or over-qualification of potential employees in the accessible labor market, which includes the unemployed.

Below, we first consider how skills requirements for any sector can be determined through the occupational profile determined in Section 2 above. We then consider how this skills requirement

[6] The authors note that skills are made up of both an explicit component (as measured through education, for example) and a tacit component (such as knowledge of markets, logistics processes, and networks, for example). However, the quantification and measurement of tacit skills raises significant challenges. To this end, where skills enter the analysis of this paper, we deal specifically with explicitly measurable skills, such as education.

profile can be used to determine a skill gap both for a sector, and also from the perspective of someone who is young and lacks the requisite skills for employment in the sector.

4.2 Identifying skill requirements

The methods outlined in the previous section provide a list of occupations for the sector in line with that sector's employment potential as an output. That list can be thought of as a list of occupational requirements for that sector. However, to determine a skill gap, the list of occupations needs to be mapped to the skills that are required for those occupations. Here, we consider how this can be done.

Skill requirements for different occupations can be defined and measured in a number of different ways. The most readily available source of information to determine skill requirements of occupations is **labor force surveys**. These surveys can be used to identify workers in that occupation, and the skills that they have according to some proxy of skills captured in the labor force survey. While not often skill-orientated, these types of national statistical surveys commonly include the indirect skill measure *qualification*, as measured by level of educational attainment. These data are likely to be collected for both employed and unemployed individuals, making it useful when measuring skill gaps that require an indicator of the skill level of the entire labor market. In the case of labor force surveys, occupation-specific skill requirements can be approximated by the average level of education by occupation classification.

Box 7: Challenges in using labor force survey data from African countries

A challenge often faced when conducting evidence-based labor market research is a lack of available labor market data that is collected at regular time intervals. Based on a sample of 41 sub-Saharan African countries, only eight have conducted labor force surveys since 1990: Botswana, Ethiopia, Kenya, Namibia, Tanzania, South Africa, Zambia and Zimbabwe. Of these, four have no data post-2006, with data being limited to two waves for all countries other than Namibia and South Africa. This lack of accessibility to high-frequency labor force data is a hindrance to time-series-type analysis, which is particularly relevant when assessing the impact of policy interventions on labor market characteristics.

In cases where these types of surveys are conducted, it should also not be assumed that these data are sufficiently accurate for use in empirical labor market research. Using the number of articles published using labor force data existing in sub-Saharan Africa as a proxy for data quality, excluding South Africa, there have been just two published research reports (based on data from Zambia and Zimbabwe) and three published journal articles (using surveys from Botswana and Ethiopia).

As a result of infrequent and poor-quality labor force data from countries in sub-Saharan Africa, researchers are often reliant on data collected by international bodies, such as the International Labor Organization. While this strategy allows the appropriate analysis to be undertaken even when countries lack their own collected survey data, a possible consequence of this practice is that national statistical institutions may be disincentivized to conduct their own labor force surveys in the future. These limitations should be borne in mind in the application of this method to developing countries in Africa.

Using such large-sample existing data is attractive, as desktop research can be conducted relatively quickly and at little cost. In addition, sources of publicly available labor force survey data exist for both developed and developing countries, though the latter to a lesser extent. For example, databases such as those managed by the International Labor Organization (ILO) have compiled labor force survey data for 160 countries, including approximately three-quarters of African countries. However, these surveys are often not skill-oriented, and many may not contain the skill proxy that the researcher has deemed most appropriate for their purposes.

Measuring skill competencies beyond a proxy for skills related to education can, however, be more difficult. Skill capabilities can be measured in different ways, and we are often limited by data availability in this regard as well. In addition to education-related measures, proxies for skill can also include measures related to knowledge and abilities. Table 15 below shows the usefulness and limitations of skills measures related to these three types of proxies (education, knowledge, and ability) for skills in the context of occupational skills requirements.

Table 15. A comparison of the usefulness and shortcomings of skill indicators: knowledge, skill, ability, and education

Skill indicator	Usefulness	Shortcomings
Skill: the capacity to make use of knowledge to perform a given role	• Includes capabilities acquired outside of formal education and training i.e. experience and on-the-job training	• **Hard to quantify**, requiring the use alternative indicators • Data **not readily available,** requiring skill-specific surveys
Knowledge: "a body of facts, principles, theories, and practices" (Eurostat, 2016)	• Indicator of the kind of education and training activities that, when applied, enable a worker to perform their specific role	• The level of understanding of a subject does not indicate the extent to which these concepts can be practically applied
Ability: the possession of a skill required to perform a specific activity	• Measure of innate traits that are independent of education, training, and experience	• No direct link between abilities and specific job-tasks
Qualification: educational attainment	• Important signal of skill level • Commonly available in labor force survey data • Can be used to map a specific occupation to a single skill requirement, requiring only one skill gap to be determined	• Does not provide information on skills developed outside of specific education programs • Comparability is limited due to heterogeneity in the quality of education

Education is the most easily observed of these skill proxies and can readily be obtained (at some level of detail at least) through labor force survey data. While easily accessible, it is questionable whether education alone can tell us anything distinguishably meaningful about the skill requirements for particular occupations. Specifically, it is commonplace for employers to stipulate that applicants have certain soft skills that are not observable when using qualification as a proxy for skill. The value of soft skills in the labor market should not be underestimated. These capabilities have been found to be predictors of success in finding employment; the pursuit of further education and training; and other socio-economic outcomes, including health and psychological well-being (Heckman and Kautz, 2012).

An emerging approach to determining skill requirements both within and across countries, is the use of **firm-based skill surveys** (Eurostat, 2016). A firm survey may contain both a quantitative and qualitative component, though there is no widely accepted method for skill-based surveys. The quantitative approach is necessary to acquire skill data, including soft skills, in a form that can be compared across firms. Supplementary unstructured interviews provide more in-depth insights into the firm- and product-specific skill requirements that, for the sake of brevity, cannot all be captured in a generic skill survey for a basket of products. This is also an opportunity to question employers about potential skills that may be required to fill future positions, with a particular focus on the opportunities within their firms that require digital skills such as computer usage and information processing. Desktop research into the skills already established to be important for the types of firms in the sample provides a good starting point for survey design. Discussing the issues around skills with industry experts could also prove useful, as their opinions may help pre-empt topics of interest to the participants of the study.

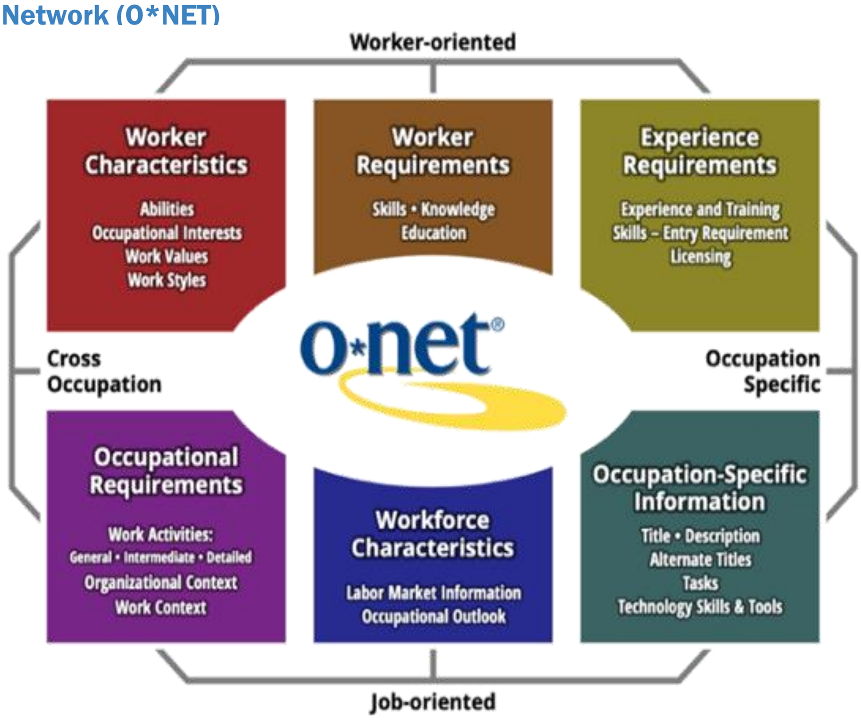
There is value in surveying both employers and employees. Employers are in a position to identify the type and level of skill they feel necessary for types of workers and where the gaps are in their existing labor force. Keogh and Stewart (2001) identify skill requirements within firms by conducting structured interviews with employers in which they were asked to identify the type and level of skill they felt necessary for types of workers, and where the gaps were in their existing labor force. McGuinness and Ortiz (2016) extended this method by supplementing employer responses with employee interviews in which they were asked about their perception of the kind and level of skill required to perform their role, offering another perspective on the skill requirements for a given job type. Depending on the level of detail required from the employer regarding the types of jobs making up their labor force, these job types can be mapped to certain occupations, with both employer and employee responses being used as indicators of the skill requirements associated with each.

There are limitations to basing a skill analysis on existing non-skill specific data sources. For this reason, there is an incentive for researchers to conduct their own surveys to identify the skill requirements of certain occupations. However, conducting surveys is labor-intensive and time consuming, often necessitating the costly employment of external survey firms. Another consideration is the comparability of survey results based on responses that are largely subjective (OECD, 2017).

The problems associated with skill proxies obtained from labor force survey data, and the infeasibility of using firm surveys to determine skill requirements can be overcome through the use of a **standardized database of skill indicators** such as the Occupational Information Network, **O*NET**. This database maps occupations to a standardized database of skill indicators and overcomes the key gaps in the use of firm survey data: the lack of harmonization in both the method of data collection, and the definitions of occupations and skills as understood by participants (Eurostat, 2016).

O*NET links occupations to information such as knowledge, skills, abilities, and education required of workers employed in these roles. The O*NET database comprises nearly 1,000 occupations and is the main source of information on occupations for the United States. It is freely available via a searchable online platform (O*NET, 2019). The O*NET data was initially constructed using the inputs of occupational analysts, and is continually updated based on survey responses from workers in each occupation as well as occupation specialists (O*NET, 2019). Figure 7 illustrates the content model of the O*NET database.

Figure 7. Data available through the Occupation Information Network (O*NET)



Source: O*NET (2019).

Any of the information related to knowledge, skills, and education can be used as a proxy for skills. However, it is important to note that if the data is used to assess skill gaps, a relevant indicator of the type of skill proxy used to determine the skill requirement for an occupation or sector must be available for the supply of labor as well. We discuss this in more detail in the next section.

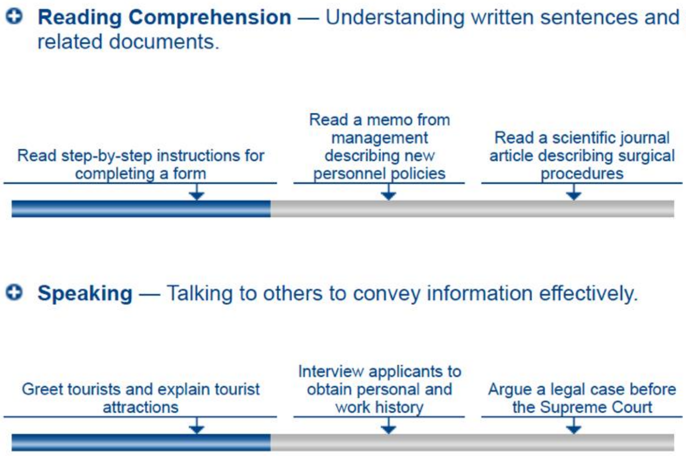
A concern is that the database uses the Standard Occupational Classification (SOC), which is not standard practice in many countries—including many in Africa. In addition to cross-country differences in occupation classification, there is often within-country variance over time. To overcome these limitations researchers have developed "crosswalks" matching their survey's coding to that of O*NET. For example, the Institute for Structural Research (IBS) in Poland provides a crosswalk of O*NET's SOC codes to the International Standard Classification of Occupations (IBS, 2016). This strategy has been adapted for the South African case by Bhorat et al. (forthcoming) and can be adapted for other countries as well.

It should also be noted that the O*NET occupational classifications provide information about occupations at the current point in time. They are, however, regularly updated and thus provide a reasonable estimate of the skills required for particular occupations—even bearing in mind that they may not be fully reflective of the skills that will be required for occupations in the future.

Box 8: Scale measures used in the O*NET database

Occupational analysts compute these scale measures for each element using inputs such as the importance, level, and relevance ratings given by the workers surveyed, and the nature of the position (O*NET, 2018). Importance is ranked between 1 and 5, with 1 being "not important" and 5 being "extremely important." Level is rated between 0 and 7 and quantifies the degree, or position along a continuum, to which a particular task is needed to practice an occupation. The following diagram provides extracts of this level continuum for the "reading comprehension" skill for "light truck or delivery services drivers."

Figure 8. Level continuum for specific skills in O*NET



Source: O*NET (2019).

For education level, employer surveys ask each participant to indicate an education level for a given occupation based on 12 categories. These scores are aggregated, with the total for all levels of education being normalized to 100, with the individual education levels being represented as a percentage of this total. In some analyses, these 12 levels have been aggregated to form broader categories.

Box 9: Examples of O*NET output for a specific occupation (light truck or delivery service drivers)

Table 16 and Table 17 provide extracts from the O*NET database for knowledge, skills, abilities and education relating to "light truck or delivery service drivers." Each of these dimensions have individual elements, which are rated according to the scales explained in Box 8. Combining these scales to obtain a single scale measure for each element has been done in numerous ways. For example, the OECD (2017) used the product of importance and level to obtain an indicator of skill intensity. In the case of education, the average data value can be used as a scale measure for the level of qualification required by an occupation.

Table 15. Knowledge, skills, and abilities required for light truck or delivery services drivers

Element name	Scale name	Data value
Knowledge		
Administration and management	Importance	2.58
Administration and management	Level	2.24
Economics and accounting	Importance	1.49
Economics and accounting	Level	0.97
Skills		
Negotiation	Importance	1.88
Negotiation	Level	1.62
Instructing	Importance	1.88
Instructing	Level	1.62
Abilities		
Oral comprehension	Importance	3.12
Oral comprehension	Level	3.25
Written comprehension	Importance	3.12
Written comprehension	Level	3

Table 16. Education level required for light truck or delivery services drivers

Element name	Aggregate category	Years of schooling	Data value
Less than high school	Less than high school	11	22.83
High school diploma	High school diploma	12	74.63
Post-secondary certificate	High school plus	15	0
Some college courses	High school plus	15	2.54
Associate's degree	High school plus	16	0
Bachelor's degree	Bachelor's degree	16	0
Post-bachelor's degree	Bachelor's degree plus	18	0
Master's degree	Bachelor's degree plus	18	0
Post-master's certificate	Bachelor's degree plus	19	0
First professional degree	Bachelor's degree plus	19	0
Doctoral degree	Bachelor's degree plus	20	0
Post-doctoral training	Bachelor's degree plus	20+	0

Source: O*NET (2019). Years of schooling adjusted from structure of education in the United States.
Note: The highest number of possible years less than high school, 11 years, is used as years of schooling for less than high school.

The use of the O*NET database provides a standardized method of mapping occupations to skill requirements, as well as making a variety of skill proxies available to researchers, allowing for results to be more tailored to the needs of policymakers than other possible methods. A further advantage of the O*NET approach is the potential to create composite skill proxies based on a combination of skill measures. For example, a study by Firpo, Fortin, and Lemieux (2011) uses a composite measure of skill and task content constructed using both O*NET and country-specific task-based surveys in order to identify task content variables. In doing so, they made it possible to extract information such as the "information content" task category, which can be used to isolate occupations from O*NET that require skills such as analyzing data, interacting with computers, and processing information. In this way, O*NET can be used to identify occupations that are intensive in digital skills.

However, the point must be made that O*NET is based on the opinions of occupational analysts in the U.S., raising the question of its applicability to developing countries. Hardy, Keister, and Lewandowski (2018) empirically tested this concern by calculating Acemoglu and Autor's (2011) version of the aforementioned composite task measures for both developed and developing countries and comparing the results. It was found that task content measures were largely consistent with those based on O*NET data, providing greater certainty that using O*NET to determine skill requirements in developing countries is generally appropriate.

A final method and source of data for determining skills requirements for specific occupations is **online job advertisements.** Kennan et al. (2008) and Hong (2016) use content analysis software to obtain the frequencies and trends of skill requirements listed by employers for a specific sector. Indicators of skills that may be obtained from this exercise are the required level of education, experience, knowledge or field of study, as well as the types of soft skills that are relevant to the position. The usefulness of this approach is determined by the ease with which this proprietary data is attainable from these job search platforms, and in what form. For the countries under assessment, it is, however, unlikely that there will be a sufficient coverage of jobs online for the use of this method.

We have thus considered four different sources of data for mapping skill requirements to occupations. The usefulness and shortcomings of each of these are noted in Table 18 below.

Table 18. A comparison of the usefulness and shortcomings of methods to determine skill requirements

Skill requirement method	Usefulness	Shortcomings
Labor force data	• Research conducted quickly with few resources • Many publicly available surveys for developing countries	• Not focused on skills and may not contain the desired skill proxy • Quality of labor force survey data not consistent across African countries
Job advertisements	• May include a number of skill proxies if advert sufficiently detailed	• Limited by the availability of data from private job search online platforms
Firm surveys	• Provides a skill-specific data source	• Labor intensive and costly • Results may not be comparable as self-reporting • Lack of harmonization in survey method as well as definitions of occupations and skills used

O*NET	• Standardization of definitions of occupations and skills • Variety of skill proxies that may be combined to form composite skill proxies • Includes direct measure for skill	• Crosswalks may be needed by individual countries • Information based on U.S. employee surveys (though empirical evidence suggests this may not be a limitation)

Ultimately, what method is used will depend on the availability of data for the sector and country being considered, as well as the intended use of that data. Firm surveys allow for skill-based information based on one's particular needs, but are costly and time-consuming. However, responses are often incomparable both within and across countries due to a lack of commonly accepted terminology and survey approach. Labor force survey data is the most widely available and easily accessible information source, but again suffers from inconsistencies in the way in which data is collected. Data quality is also an issue making some cross-country comparisons infeasible. Labor force survey data also provides a skills proxy based on education only, which may not provide an ideal level of skill requirement detail. While the O*NET database is also based on surveys of the labor force, the standardization of responses by occupational analysts provides a source of multiple skill proxies that can be used for cross-country comparisons, with those for developing countries being generally accepted. Consequently, despite any challenges that may be faced when developing a suitable crosswalk, O*NET is one of the most reliable sources of information that can be used to map occupations to their skill profile. We would thus suggest using a standardized database such as O*NET to map skill requirements for occupations in specific sectors, if there are no major concerns with using this method in the specific country or sector being considered.

4.3 Measuring skill gaps

Having determined the skills requirements for a sector to obtain its employment potential through the use of the employment potential consistent occupational profile, we can proceed to identify whether the skills required are available in the target population. Where the skills do not currently exist, this is indicative of a skill gap that needs to be addressed for the sector to be able to reach its potential.

Skill gaps can be measured in terms of any of the skill measures or proxies mentioned above. However, the extent to which it is possible to measure this gap will be dependent on whether equivalent data relating to the proxy for skills is available for the targeted supply of labor.

It is relatively easy to obtain the necessary data for an education- or qualifications-based measure of skills. As we discussed above, labor force surveys would include some measure of education or qualification for the labor force, including those who are unemployed.

It is, however, more difficult to obtain an indication of the level of skills for the broader labor force for measures related to knowledge and ability rather than solely to education. A possible approach here would be to conduct a **survey designed to measure skill capabilities** among the target population (the youth), in the same way the skill requirement has been measured for occupations. In this way, measures of specific skills could be obtained rather than having to use education as a skill proxy, a measure that is not designed to capture the skill distribution of unemployed youth with the same qualification. This approach is of particular relevance when considering soft skills, bearing in mind their importance when determining the employability of this population. This exercise would, however, be time and resource intensive. Furthermore, the results of such a survey may not be reliable given that it may not be possible to adequately assess the work-related skill level of a group of individuals that have likely never participated in the work force before.

We proceed to discuss the measurement of skill gaps here on the basis of an education-based measure only. It should be borne in mind that the gap measures noted here can be computed for other measures of skills, should an appropriate base indicator of skill in the population be estimated. One need simply substitute the skill requirement as defined by the knowledge- or ability-based skill measure for the education-based skill measure, as well as substitute the appropriate indicator of the skill measure in the population for the education-based skill indicator for the population.

We discuss two measures of a skill gap here: a sectoral skill gap and an occupational skill gap. The first measure of skill gap relates the skill requirements for a sector to the availability of skills in the country in the target population (youth). This sectoral skill gap can be illustrated by the set of equations below.

$$S = [s_1, \quad s_2, \quad \cdots \quad s_j] \quad D = [d_1, \quad d_2, \quad \cdots \quad d_j]$$

$$S - D = [(s_1 - d_1), \quad (s_2 - d_2), \quad \cdots \quad (s_j - d_j)]$$

Single row matrix, S, represents skill supply with the number of youth being separated in education cohorts. Similarly, single row matrix, D, illustrates the number of workers required in each education cohort for a single sector, calculated by summing the individuals required in each skill level for all occupations in the industry. Subtracting matrix D from matrix S gives a matrix of the skill gap, or the shortage/surplus of workers for each level of skill.
More concretely, this gap can be represented as in Table 19 below, where B is the level of education cohort and A is each occupation required in the sector.

Table 19. Skill requirements, skill supply, and sectoral skill gap by education level

	$\boldsymbol{B_1}$	$\boldsymbol{B_2}$	$\boldsymbol{B_3}$	$\cdots$	$\boldsymbol{B_j}$
Skill supply	s_1	s_2	s_3	$\cdots$	s_j
Skill requirement	d_1	d_2	d_3	$\cdots$	d_j
$\boldsymbol{A_1}$	m_{11}	m_{12}	m_{13}	$\cdots$	m_{1j}
$\boldsymbol{A_2}$	m_{21}	m_{22}	m_{23}	$\cdots$	m_{2j}
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$
$\boldsymbol{A_i}$	m_{i1}	m_{i2}	m_{i3}	$\cdots$	m_{ij}
Sectoral skill gap	$(s_1 - d_1)$	$(s_2 - d_2)$	$(s_3 - d_3)$	$\cdots$	$(s_j - d_j)$

With respect to the skill supply, an example of the distribution of skills for the South African unemployed youth by level of education is shown in Table 20.

Table 20. Skill supply of unemployed youth (15-24 years old), by level of education, South Africa 2018Q3 (in thousands)

	Less than secondary	Secondary complete	Post-secondary	University degree
Skill supply	1,302	999	101	32

Source: Statistics South Africa (2019a).

The table shows that there were 2.4 million unemployed youth in South Africa in Quarter 3 of 2018. Of these, 1.3 million had less than secondary education, around 1 million had completed secondary education, 100,000 had post-secondary education, and 32,000 had a university degree.

To calculate the skill gap for any particular sector relative to this stock of skills in the target group, then, one would need to compare this total stock of skills to the skills required by the sector. However, it is important to note that it is only possible to measure this type of skill gap if the number of workers required in each education cohort can be estimated (as this is what will need to be compared to the skill supply). Measuring the skill gap in this way will be dependent on being able to estimate an occupational distribution for the sector in the estimation of potential employment stage of the method. Depending on the approach used there, one might only obtain a list of necessary occupations and not a precise estimate of numbers required for each occupation. In this case, this sectoral skill gap will not be able to be estimated.

Using the current distribution of occupations in the horticultural sector (using the 3-digit classification to identify individuals) as an example, we illustrate in Table 21 how the sectoral skill gap can be calculated.[7]

Table 17. Illustrative example: Estimating the sectoral skill gap for the horticultural sector in South Africa based on the current occupational distribution

	Less than secondary	Secondary complete	Post-secondary	University degree
Skill supply	1,302	999	101	32
Skill requirement	95	83	14	11
Managers	5	9	3	7
Technicians	3	4	0	0
Clerical workers	1	7	2	0
Services and sales workers	3	1	0	0
Skilled agriculture	13	8	1	3
Craft and trades	17	1	1	0
Plant and machine operators	35	10	0.5	0.6
Elementary workers	0.4	43	6	0
Skill gap	+1,207	+916	+87	+21
Skill availability ratio	13.7	12.0	7.2	2.9

Notes: All numbers are thousands of individuals. The skill surplus is positive, while the skill shortage is negative.

For each identified occupational category (here we have used the standard nine category broad classification for illustration), we show the number of individuals with varying levels of education. The existing distribution of educational attainment across categories is taken as the skill requirement for the sector in this example. If available, any other measure of skill can be used as

[7]We note here that the current distribution is not reflective of the employment potential of the sector – and in our application of the method the relevant occupational distribution (as well as occupational categorization) will depend on the results of the first part of the method where potential employment is estimated. We present the example here based on current occupational distribution for one sector as an illustrative example only.

well. Adding up all of these per education (or skill) category gives a total skill requirement for that education (or skill) category. Subtracting the total skill requirement from the skill supply for that education category then gives an indication of the sectoral skill gap for the sector (that is, the extent to which the skills required in the sector, by a number of skills categories, exists in the target population). In our example, based on the assumed skill requirement distribution, there is no skill gap in the horticultural sector, with a skill surplus ranging from 21 for degrees, to 1,207 for less than secondary education.

A limitation of the sectoral skill gap is that it only notes whether the skills exist in the target population as a whole. Thus, it does not take into account that not all of the target population will be employed in this specific sector; the skill base will need to accommodate other sectors as well.

An alternative skill availability ratio for the sector (illustrated in the last row of the table above) may be useful in this case as a broader indicator of skill availability. This ratio measures the skills that exist in the population against the skills required in the sector for each of the skills categories. It is a measure of the extent to which the required skill exists in the target population. When it is large, one can be confident that the skills required for the sector will be able to be accessed in that sector particularly. However, if the ratio is considerably smaller (less than 10, for example), it may indicate that, despite the skills being available in the wider population, there are concerns about whether those skills will be able to be attracted to the sector under consideration in particular. In our specific example, the skill availability ratio for degrees is concerning given that the number of unemployed degree holders is only three times higher than the degree skill requirement for the sector. Given that degree holders will seek employment in other sectors as well, it is not likely that this availability will be high enough to accommodate the degree needs of this sector in particular.

Given the limitations of this type of skill gap, we also propose estimating a second occupation specific skill gap. In this case, the skill gap can be calculated as the difference between the skill requirement for a given occupation and the national modal education level, as measured by years of schooling (or other skill-specific measure if appropriate) of the youth.

This measure is indicative of the extent to which an individual is under- or over-qualified for a given role in a particular industry. This approach has the added value of allowing occupations to be ranked according to the types of jobs with the biggest misalignment in skills.

In equation form, for each occupation *i*, we would have a skill requirement as per the chosen measure of skill, R, and this would then need to be compared against the typical youth's skill level according to that measure, Y. For any occupation *i*, the skill gap can then be represented as

$$Y - R_i$$

A negative gap indicates that there is gap that needs to be filled to meet the occupational skill requirement for the typical unemployed youth, while a positive number suggests that the typical unemployed youth already has the skills required for that occupation.

An example is given in Table 22 for the occupational skill gap for a number of key occupations in the agricultural industry in South Africa. Based on modal years of education[8] as the measure of youth skills (Y), as well as the measure of occupational skill requirement (R), there is a skill gap for two of these three occupations: soil and plant scientists (nine years) and water resource specialists

[8] For this example, based on years of education, the educational qualification most frequently observed for the group is used to calculate the modal years of education for the youth and the occupation. Based on LFS data, we obtain the modal years of education for unemployed youth as the category of education that occurs most frequently in the data. Based on O*NET, we obtain the modal years of education for an occupation based on the qualification that is observed most frequently for that occupation. We first obtain the qualification that is observed most frequently for the occupation. The qualification is then mapped to the corresponding number of years of education to obtain a modal years of education measure for the occupation.

(four years). There is, however, no gap for farm workers. The occupations are listed and ranked in the table from largest to smallest gap indicating where considerable action will need to be taken to bring the average youth's skills level to that required by each occupation.

An advantage of this approach is that it does not require a precise measurement of the number of individuals that will be required to be employed in each occupation. A list of sector-specific occupations obtained from the potential employment estimation exercise will suffice for the estimation of this type of skill gap. However, the measure can readily be adapted to give a more precise sectoral skill gap measure, should this be required. Should the number of required individuals per occupation be known, all that will be required will be to multiply the number of individuals by the gap for each occupation, and to sum up all of these for the sector.

Table 18. Occupational skill gap for the unemployed youth, by years of schooling, South Africa 2018Q3

Occupation	Skill supply	Skill requirement	Skill gap
Soil and plant scientists	11	20	-9
Water resource specialists	11	15	-4
Farmworkers	11	11	0

Sources: O*NET (2019); Statistics South Africa (2019a).

On the labor and skill supply sides then, the method ultimately aims to do two things. The first is to assess the current stock of skills in the target population (youth). The second is to use this to calculate skill gaps for the sector being considered and the target population. Both of these gaps are important to assess in order to address the youth skill gap in a way that skills on the supply side are able to meet the type of labor and skills required on the demand side.

5. Summary of method

The key steps of the method, as well as how they relate to each other within a skills supply and demand framework, can be seen shaded in green in Figure 9.

These steps are summarized below:

Step One: Estimate potential employment of sector

This is the first of three steps on the demand side, and there are two possible approaches.

Approach A: Use existing data (growth trends and labor intensity measures) to project employment in the sector.

Approach B: Conduct a value chain analysis of the sector identifying opportunities to unlock growth, and use a survey to estimate the number and type of jobs that will be created in the sector.

Step Two: Obtain profile of sector's occupational requirements based on estimate of potential employment

If Approach A above is used, use trends in the occupational distribution of the sector to obtain a distribution of occupations for the projected employment.

If Approach B above is used, use the results of the estimation to adjust the current occupational profile of the sector accordingly, and obtain a list of occupations in the sector or a list of occupations and number of individuals required for each identified occupation in the list. (The level of detail obtained from Approach B will depend on the depth of work undertaken under this survey-based approach).

Step Three: Determine skills requirements of sector based on occupational profile obtained in Step Two

Here, the occupations and occupational distribution obtained in Step Two must be mapped to an appropriate measure of skills. We suggest using a standardized occupational-skills mapping standard. We make use of O*NET. This standard contains information related to various measures of skill and can be easily used for other countries through the use of an appropriate crosswalk.

Step Four: Identify skill gaps based on the skills requirements of the sector and the stock of skills in the target population (youth)

The final step relates to the supply side and consists of two components with the ultimate aim of identifying skill gaps for the sector and target population. Step 4a is determining the stock of skills in the youth population. Step 4b is applying the measure of stock of skills and the measures of sectoral skills requirements to obtain the following skill gaps:

i. Obtain **sectoral skill gap** by subtracting the sectoral skills requirements from this stock of skills for each type or level of skill identified.

ii. Obtain **occupational skill gaps** by subtracting the skill level of a representative youth from the occupational skill requirement for each relevant occupation required in the sector.

Table 23 summarizes the three steps of the method on the demand side, as well as the data requirements, while Table 24 summarizes the relevant steps of the method on the supply side. Note that two approaches are presented for the demand-side table. However, only one approach is presented on the supply side as the gaps noted are applicable to both of the possible approaches for the method on the demand side.

Figure 9. Representation of framework for method to identify skill gaps in the youth population

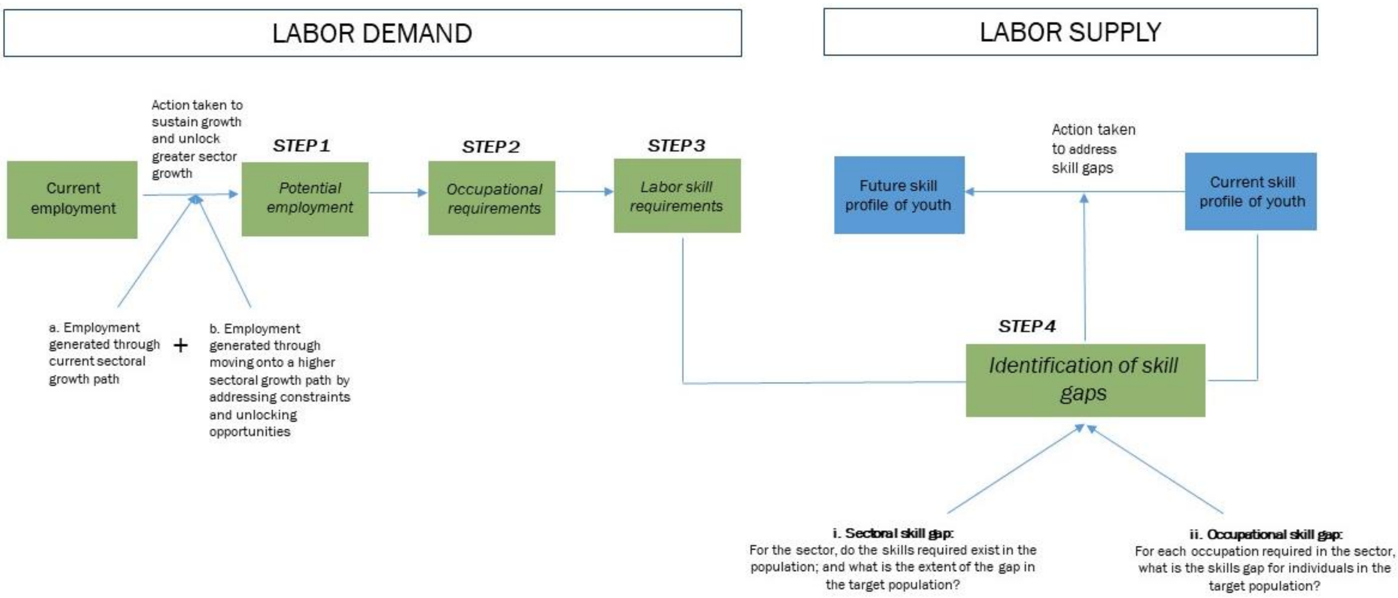


Table 19. Summary of the labor and skills demand components of the method, by approach

	LABOR AND SKILLS DEMAND		
	Step One	**Step Two**	**Step Three**
	Estimate potential employment of sector	**Obtain profile of sector's occupational requirements based on estimate of potential employment**	**Determine skills requirements of sector based on occupational profile obtained in Step Two**
Approach A: Employment projection	Use measures of labor intensity and growth trends to estimate employment at some point in the future	Use trends in the occupational distribution of the sector to obtain an occupational distribution of the estimate of projected employment obtained from Step One	Map occupations to skills using a standardized occupational-skills standard. Choice of proxy of skill is dependent on the researcher's need and data availability.
Data required	Labor Force Survey data, Input-Output tables (dependent on approach used)	Estimate of potential employment from Step One; Historical labor force survey data	List and distribution of occupations from Step Two; O*NET; possibly a relevant crosswalk
Output obtained	An estimated number of jobs in the sector at some point in the future	A distribution of the number of jobs according to occupational categories	A profile of skills requirements for each relevant occupation identified in the sector; a corresponding distribution of skills requirements for the sector
Approach B: Value chain analysis	Conduct a value chain analysis of the sector identifying opportunities to unlock growth	Identify opportunities to unlock growth and use a survey and other relevant data to estimate the number and type of jobs that will be created in the sector should the growth be unlocked	Map occupations to skills using a standardized occupational-skills standard. Choice of proxy of skill is dependent on the researcher's need and data availability.
Data required	Desktop research, input-output tables, existing and own surveys	Estimate of potential employment and list of occupations and numbers of required individuals from Step One; Historical labor force survey possibly to supplement the results of own surveys	List and/or distribution of occupations from Step Two; O*NET; possibly a relevant crosswalk
Output obtained	Depending on depth of work, either a list of relevant occupations in the sector OR a list of relevant occupations with the required number of individuals for each occupation	A list of occupations OR a list of occupations with the required number of individuals for each occupation	A profile of skills requirements for each relevant occupation identified in the sector; a corresponding distribution of skills requirements for the sector

Table 20. Summary of the labor and skills supply component of the method.

	LABOR AND SKILLS SUPPLY	
	Step 4a	**Step 4b**
	Determine stock of skills in the target population (youth)	**Calculate skill gap**
Skill Gap i: Sectoral skill gap	Determine stock of skills in the youth population by relevant skills categories	Obtain sectoral skill gap by subtracting the sectoral skills requirements from this stock of skills for each type or level of skill identified
Data required	Labor Force Survey data	Skills requirements from Step Three and skill supply profile from Step 4b
Output obtained	Distribution of skills in target population by skill category	Sectoral skill gaps for each category of skills considered
Skill Gap ii. Occupational skill gaps	Determine skill level of the average, median or modal youth in the population (as an appropriate measure of the skill level of a typical young person)	Obtain occupational skill gaps by subtracting the skill level of the average youth from the occupational skill requirement for each relevant occupation required in the sector

Data required	Labor Force Survey data; own survey possibly (for skill level of a representative youth)	Occupational skills requirements from O*NET and measure of skill level of a young individual from Step 4b
Output obtained	The average, median, or modal skill level of the youth (as appropriate)	Occupational skill gaps for the youth for each relevant identified occupation in the sector

6. Conclusion

We have presented a methodological framework for assessing the extent to which youth unemployment can be addressed through employment creation in industries without smokestacks in individual countries, as well as the skill gaps in the youth population that need to be addressed for this potential to be reached.

There are two main components to the method: Estimating sectoral skill demand, and identifying skill gaps in the target population to match sectoral demand. In terms of labor demand, we suggest estimating potential employment, occupational requirements, and skill requirements for a particular sector, while for our understanding of labor and skills supply point to the identification of skill gaps for the youth in line with the estimate of potential employment. The occupational profile obtained from the estimate of potential employment is the key link between the demand and supply sides, as it is derived from the potential employment estimate used as an input to obtain an estimate of skills requirements for an industry. Our ultimate aim is to determine the gap between the skills required for the occupations identified through the potential employment component of the exercise on the demand side, and the skills available in the target population on the supply side (youth).

On the labor demand side, we attempted to answer the following question: *What skills are required for the sector to reach its employment potential?*

We provided an assessment of the employment potential of the sector. Should employment growth in the sector continue to grow in line with past performance and the prevailing labor intensity of output in the sector, potential employment in the sector can broadly be estimated at some point in the future based on this. We have presented a number of methods to do this using measures of labor force intensity for a sector, such as labor-value added ratios and employment elasticities.

We also considered how future employment may also be greater than that projected, based on current demand and trends in demand if constraints to growth in the sector are addressed and opportunities for growth in the sector are unlocked. We presented a global value chain-based approach to make an assessment of potential employment in this regard. This approach, however, requires the extensive use of surveys and in-depth sectoral research and may not be feasible to conduct within the context of this project.

Our approach has a strong emphasis on the occupational requirements of sectors, and, based on the assessment of potential employment in the sector, we present methods for determining the occupational requirement profile of the sector based on the potential employment estimate obtained. Broadly, these methods involve estimating a profile of the occupations (and number of individuals required per occupation if the approach used allows this) based on the potential employment estimate.

Having presented how to estimate the potential employment in the sector and the occupational profile in line with this, we proceeded to present the component of the method that focuses on skills. Still on the demand side, we first consider the labor skills requirements for the sector to meet the projected future demand obtained from the estimate of potential employment. The skills requirement profile is based on the occupational profile and relates the set of occupations required for the sector to reach its employment potential to a measure of skills such as education.

Having presented how to determine demand for skills in the sector, we turned our attention to the supply of skills. Here the method aims to answer following questions for a particular sector: *Do the skills to meet the demand in the sector exist in the target population; and if not where are the gaps?*

Using the skills requirement profile for the sector, we noted how we can consider whether the skills to meet a sector's skills requirements exist in the target population (youth); and where the youth may currently be lacking in respect of the skills required by the sector.

We identified two types of skill gaps. The first skill gap is a *sectoral skill gap,* an indication of the gap between the set of skills available in the population and the set of skills required by the sector. It should however be noted that this skill supply of the population will not only be for the requirements of that one sector in particular, but may also be required by other sectors.

The second is an *occupational skill gap* identified for each occupation that relates the skills requirement for each occupation of importance identified for the sector to the skills level of the average unemployed youth.

Both these gaps are important for assessing the extent to which there is currently a skills deficit in the target population for any particular sector, and taking appropriate action to address that gap so that the youth can attain the skills to be able to participate in the sector—and enable the sector to reach its potential.

We have highlighted difficulties that may be encountered in applying the method and approaches suggested in this document for developing countries. These relate to availability and quality of data; as well as the scope and budget required to implement some of the methods suggested.

One limitation of the method that we draw attention to here in conclusion is that while it can be applied to a number of skills measures related to education, knowledge, tasks and abilities (as mapped to occupations in O*NET), it is likely that, without conducting one's own survey to construct an equivalent measure of skills for the target population (youth), we will only be able to estimate skill gaps based on education level only. This limitation exists because the most readily available source of data for the exercise is labor force survey data, which typically only contains education related data as a proxy for skill.

For the full potential of the method to provide insights on skill gaps to be realized, appropriate measures of non-education-related measures of skills will be required for youth. Overall, however, the methods presented here can be used to obtain measures of the identified skill gaps that will be useful for policymakers, even if these are limited to education-based measures of skill at this point.

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