ANNEX D Indicators and sources of data on rural youth employment

Introduction

High-quality data are a prerequisite for informed discourse on rural youth. Yet limitations in data availability and quality remain a serious issue in developing countries, in general, and in rural areas, in particular. This annex provides an overview of data availability and key data challenges in two areas of crucial importance for the life outcomes of rural youth: labour market outcomes, most critically employment, on the one hand, and education and skills, on the other. The focus is on individual-level indicators and data collected via sample surveys. For more comprehensive primers on the content and source of labour statistics, the reader is referred to publications of the International Labour Organization (ILO) such as the *Quick Guide on Sources and Uses of Labour Statistics* (ILO, 2017a).

This annex is organized as follows. Section 2 summarizes key concepts related to the measurement of employment and skills. Section 3 surveys the available data and explores the extent to which these data serve to measure indicators of interest. Section 4 closes with an overview of some of the most urgent data challenges and constraints that remain to be overcome.

Key concepts in measuring labour and skills

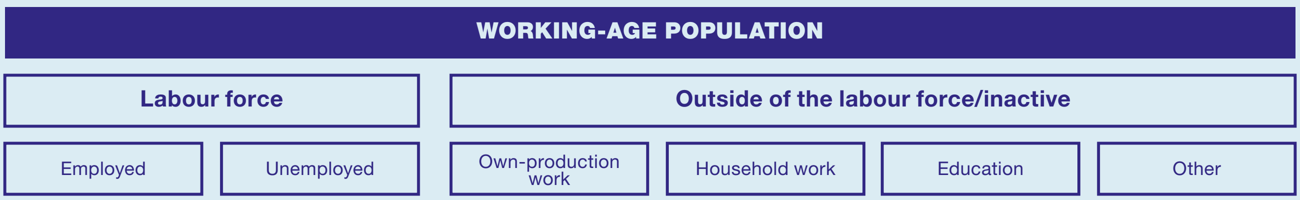
Key labour market indicators

At the macro level, the structure of the labour market defines societies. Long-term processes such as structural transformation, demographic transition and trends in international competitiveness can only be monitored with the help of aggregated labour market statistics that are consistent across countries and over time. At the micro level, the extensive body of literature about livelihoods illustrates how employment determines people's identities and living conditions (Ellis, 1998; Haggblade, Hazell and Reardon, 2007). Labour market data are therefore of key importance for the study of a host of socio-economic issues, and this is particularly the case when it comes to understanding the opportunities and challenges confronting young people (IFAD, 2016; World Bank, 2012).

The first central concept involved in measuring labour market outcomes using microdata is the trichotomy of *employed, unemployed* and *outside of the labour force*, or economically inactive. All people of working age (usually defined as from 15 to 64, or from 15 to 24 for the youth population) can be classified in one, and only one, of these categories. The sum of the employed and unemployed population equals the labour force (see figure 1).

Persons are considered *employed* if they either worked at least one hour during a short reference period (last 7 days) *for pay or profit* or were temporarily absent from their job (due to illness, vacation and so forth) (19th ICLS, resolution I,

FIGURE 1 Classification of the working-age population by employment, unemployment and inactivity status



Source: Own compilation based on ILO (2013a).

para. 27). A critical innovation in this definition relative to previous definitions of employment is the requirement that *work* be performed *for pay or profit* in order to be considered *employment*. The definition no longer classifies individuals engaging in other forms of work, notably those producing goods for own final use, such as subsistence farmers,[1] as "employed" but rather classifies them as being outside of the labour force. This change substantially alters key labour market indicators, such as the employment and unemployment rates, particularly in countries with high levels of subsistence farming (Global Strategy, 2018). It is therefore also of particular relevance to rural communities.

Many national statistical offices have not yet implemented the new definition and continue to classify persons who produce for own use as employed. One reason for this is that it is difficult to distinguish agricultural households that mainly produce for their own final use from agricultural households that mainly produce for the market (Global Strategy, 2018). The guidance provided to practitioners is to differentiate between production for profit and own-use production based on the presence or absence of an ex ante intention to sell. This is an area where there is limited experience and understanding of how the data are best captured and what the implications of different data collection approaches might be for estimates of employment. The 19th International Conference of Labour Statisticians (ICLS) also reclassified volunteer workers and unpaid trainee workers as being *outside of the labour force* rather than in employment, a definitional change that is likely to disproportionally affect statistics on youth. Likewise, unpaid domestic and care work, often a time-consuming daily activity, is not considered employment.[2] The determination of employment status in household surveys is commonly operationalized by means of an exhaustive series of binary questions covering various types of employment activities (e.g. salaried labour, own-account work, household agricultural activities, running or helping to run a non-farm household business, or paid apprenticeships). These questions are posed either to the household respondent or, preferably, directly to each individual household member above a certain age. Household surveys may also contain questions on other non-employment forms of work.

Persons are *unemployed* if they are not employed, are actively seeking a job and are available to work (19th ICLS, resolution I, para. 47). This requires at least two additional questions: one to evaluate whether the person is actively seeking a job, which is often operationalized by asking about job search strategies, and a second question to evaluate whether the person is available to work.[3] Persons who are neither employed nor unemployed are considered to be outside of the labour force. A further key labour market indicator is the share of people *not in employment, education or training* (NEET). NEET is constructed from the basic employment indicators plus standard education questions on current attendance at school or training institutions of another kind. NEET is an especially critical indicator for the youth population.

Three additional dimensions used to describe the nature and type of employment refer to its composition by *industrial sector, occupation and formality/informality*. Surveys use questions about the sector and the occupation of workers to classify jobs according to international standards. The International Standard Industrial Classification (ISIC) is used to classify jobs by sector, while the International Standard Classification of Occupations (ISCO) is used for occupational groups.

The distinction between formal and informal employment is more problematic, and discussions with a view to the revision of the international definitions of formality and informality are ongoing (most recently at the 20th ICLS). The current definition of informal employment is based on the 17th ICLS conceptual framework and includes both employment in "informal enterprises" and "informal jobs" in the formal sector (ILO, 2017c).

1 In practice, the definition of employment used by national statistical offices already varied from one country to the next before the 2013 revision of the definition of employment by the 19th International Conference of Labour Statisticians (ICLS). An International Labour Organization (ILO) paper that reviews all labour force surveys conducted between 2000 and 2010 shows that all countries include wage employment and self-employment in market units within the concept of employment, but that variation exists with regard to their classification of persons engaged in the production of goods for own use. The paper indicates that 40% of the national statistical offices define at least some persons engaged in own-use production as employed. This is particularly prevalent in the case of persons producing agricultural products for own use, whereas only a few statistical offices include persons who are constructing their own dwelling or are fetching water in their definition of employment. (ILO, 2013b).

2 To account for these activities and promote gender equality, Sustainable Development Goal (SDG) indicator 5.1 measures the proportion of time spent on unpaid domestic and care activities.

3 The ILO definition of unemployment is sometimes considered to be too restrictive (De Vreyer and Roubaud, 2013). Many persons who have been classified as outside of the labour force on the basis of the ILO definitions are available to work but have not actively been looking for a job in the last four weeks. Some authors expand the definition of "unemployment" to include this group (Brandolini and Viviano, 2006). Recently, the 19th ICLS introduced and defined the concept of the "*potential labour force*", which consists of persons outside the labour force who are either seeking a job but are currently unavailable to work (*unavailable job seekers*) or are not looking for work but who are willing and available to take up employment (*available potential job seekers*) (19th ICLS, resolution I, para. 51).

Informal enterprises are identified based on criteria that vary from country to country but that often refer to their size and legal status (e.g. whether the enterprise is registered). At the operational level, information on the institutional sector (public, private, household) is generally available, while information about firm registration is often not collected (ILO, 2018b). *Informal jobs* are defined as work activities performed without written contracts for which the employer does not pay social security contributions or any other benefit, such as paid annual or sick leave (Ruppert Bulmer, 2018). In national surveys, data on employers' social security contributions are generally available, while other data are sometimes available and sometimes not (paid annual leave) or hardly ever collected (paid sick leave) (ILO, 2018b).

Informal employment is one of 70 indicators adopted at the 18th ICLS in 2008 for measuring *decent work*, defined as men's and women's productive work in conditions of freedom, equality, security and human dignity (ILO, 2013a).[4] A number of problems tend to be encountered when attempting to collect data on decent work in household surveys, however, particularly in rural areas and in low-income countries. Household surveys do not capture all 70 of the indicators needed to measure decent work, as they rarely cover qualitative dimensions of employment (e.g. earnings, working time, treatment at work, stability/security, underemployment) (Oya, 2015). Furthermore, sampling design may underrepresent some worker categories, such as children at work, seasonal migrants and seasonal workers, and people not residing in the residential units being surveyed or who are not included on official household lists at the community level (Oya, 2015).

A further set of core labour statistics – *hours worked, average hourly earnings and average income* of small-scale producers – relate to the notion of returns to labour and is necessary to estimate labour productivity and the amount of time spent on domestic and care work.[5] A key distinction is between hours *actually* worked and hours *usually* worked. *Hours actually worked* is defined as the time spent in a job for the performance of activities that contribute to the production of goods and/or services during a specified short or long reference period,[6] while *hours usually worked* refers to a "typical" value representing the number of hours actually worked measured over a longer reference period (18th ICLS, resolution I, para. 11). Finally, the *average hourly earnings of employees* are the remuneration in cash or in kind received for time worked, while *income* refers to earnings from self-employment.

In practice, measuring income and average hourly earnings is notoriously difficult. For instance, measuring the income of own-account farmers requires collecting information on crop production, whether produced for own consumption or sold on the market and obtaining information on agricultural inputs and investments (UNECE, 2007), while measuring the income of non-farm household enterprises requires collecting data on gross revenues and subtracting costs (de Mel, McKenzie and Woodruff, 2009). Such data are generally collected at the level of the household, so assigning the income to specific individuals within the household is virtually impossible and would in any case require strong simplifying assumptions. This clearly limits the possibility of using such data to estimate the returns at the individual level of engaging in specific occupations or the returns associated with the use of given assets, including education, in different forms of employment.

Possibly the most careful attempt to derive labour productivity estimates from national household survey data is to be found in the work of McCullough (2017), which is limited to estimating average per person and per hour labour productivity measures per activity (farming, self-employment and wage employment) and per sector (agriculture, industry, services) and does not refer to any youth-specific labour productivity estimates. Work done by Gollin, Lagakos and Waugh (2014) also points to potentially large measurement errors in labour productivity measures in the case of agricultural labour and to differences in estimates between survey-based and national account estimates.

The interpretation of standard employment indicators is not straightforward in the case of the youth population. The transition from school to work is not a linear process; the starting and ending points of the transition are not well defined, as individuals may exit and re-enter school and the labour force at various points and may alternate periods of employment with periods of unemployment, and the nature of certain jobs may change. In developing

4 The framework for the measurement of decent work covers 10 substantive elements: employment opportunities; adequate earnings and productive work; decent working time; combining work, family and personal life; work that should be abolished; stability and security of work; equal opportunity and treatment in employment; safe work environment; social security; and social dialogue and employers' and workers' representation (ILO, 2013c).

5 Both labour productivity and time spent on domestic and care work are Sustainable Development Goal (SDG) indicators (SDG indicators 2.3.1 and 5.4.1).

6 A distinction is made between the actual hours worked and the usual hours worked. Actual hours worked is measured over a short reference period such as the last seven days, whereas usual hours worked refers to a "typical" value measured over a longer reference period.

countries, these issues are, if anything, even more difficult to grasp, as women's labour force participation rate is low, individuals frequently combine work and schooling, and underemployment, self-employment, home production and casual employment are widespread.

The fact that the decision to leave school is endogenous and, in turn, depends on expectations concerning the probability of successfully transitioning to work makes the understanding of this critical stage in young people's lives even more complex for policymakers and analysts and all the more challenging for data producers (Guarcello et al., 2008). Analysing this dynamic process may entail relying either on cross-sectional data or on panel data, with the latter being preferable for the creation of individual histories.

Cross-sectional household surveys may include retrospective questions designed to obtain information on individual work histories every 3 to 10 years or on an ad hoc basis. In contrast, panel household surveys track the employment and education information of family members over time at intervals of from two to three years. In order to gain a better understanding of this transition, it would also be important to build the information base needed in order to link the youth labour market situation to the demand for labour on the part of prospective employers, including information on key characteristics that define employability, starting with a varied set of skills and individual characteristics that evolve and change with advances in technology and the general organization of work and employment.

Key concepts of skills measurement

A person's level of education and skill set are a key factor in his or her life success. The literature generally distinguishes between *cognitive skills*, such as literacy, numeracy and reasoning skills, which are sometimes captured in IQ measurements; socio-emotional or *non-cognitive skills* having to do with personality traits; and *technical or job-related skills*, such as technical knowledge specific to a person's work. Evidence suggests that both cognitive ability and non-cognitive skills are predictive of socio-economic success (Heckman, 1995; Murnane, Willett and Levy, 1995; Heckman, Stixrud and Urzua, 2006; Heckman and Kautz, 2012).

Years of schooling is the most basic measure of educational attainment that is collected in most household surveys. This is an unsatisfactory measure of an individual's skills and ability because it does not account for possibly large differences in the quality of education and does not capture non-cognitive skills. It is the quality of schooling, more than its quantity, that matters for learning and life success (Altinok, Angrist and Patrinos, 2018). International or regional student assessment programmes, such as the Programme for International Student Assessment (PISA),[7] have sought to address this issue and produce comparable skills indicators by testing students' ability in such subjects as math, science and reading comprehension in a harmonized and psychometrically tested fashion when the students have reached the age of 15 and are nearing the end of their compulsory schooling (Altinok, Angrist and Patrinos, 2018). Data from these school-based test programmes are typically available at an aggregate level but do allow for disaggregation by gender, urban/rural place of residence and age. In the World Bank's Human Capital Index, educational levels are compared across countries using a measure that represents an attempt to combine the quantity and quality of education: the Expected Learning-Adjusted Years of School (Kraay, 2018). This indicator uses standardized measures of student learning, drawn from various student assessment programmes, to rescale the years of schooling indicator for cross-country comparisons (World Bank, 2017).

Cognitive skills are generally measured in surveys in one of two ways: by self-reporting or by direct assessment. In the former case, respondents self-report whether they are literate and numerate and how well they perform certain tasks. The self-reporting approach is parsimonious and simple but is subject to respondent biases and is limiting in terms of its analytical detail. There are various well-established strategies for measuring cognitive skills through direct respondent assessments. Laajaj and Macours (2017), for example, evaluate cognitive ability by letting respondents work through a series of tasks, tests and puzzles involving analytical reasoning, short-term memory, math and reading comprehension, and they conclude that cognitive skills measures are reliable and internally consistent. Several international survey programmes that employ cognitive skills testing are described in the next section.

The key concept in measuring non-cognitive skills is the *"Big Five"* taxonomy of personality traits, which rates respondents in five personality trait dimensions: *openness, conscientiousness, extraversion, agreeableness* and *neuroticism*.

7 https://nces.ed.gov/surveys/pisa/.

TABLE 1 "Big Five" personality traits

Trait	Description
Openness	Curious, original, intellectual, creative, open to new ideas.
Conscientiousness	Organized, systematic, punctual, achievement-oriented, dependable.
Extraversion	Outgoing, talkative, sociable.
Agreeableness	Affable, tolerant, sensitive, trusting, kind, warm.
Neuroticism	Anxious, irritable, temperamental, moody.

Source: Goldberg (1990).

The Big Five taxonomy is commonly operationalized using an instrument containing 44 questions in line with the work of John and Srivastava (1999). The responses are evaluated using a scale ranging from *strongly agree* to *strongly disagree* and then summarized in a score for each dimension (Pierre et al., 2014). Additional measures of non-cognitive skills commonly employed in surveys include: *locus-of-control*, intended to measure the extent to which respondents view themselves as having control over their lives relative to external forces and circumstances; *grit*, focusing on respondents' ability to persevere in pursuing their goals; and *risk and time preferences* (Pierre et al., 2014; Laajaj and Macours, 2017).

Technical skills refer to basic knowledge about how to perform a specific task, usually related to an individual's work. Technical skills are measured either through respondent self-reporting (Pierre et al., 2014) or the assessment of respondents' knowledge in a specific field, such as agriculture (Laajaj and Macours, 2017). Recent validation studies have shown that the reliability of non-cognitive skills measures is low in low-income settings, with biases that are sensitive to the answering patterns of respondents and the phrasing of the questions (Laajaj and Macours, 2017).

Sources of labour market and skills data

ILO maintains a global database of employment statistics (ILOSTAT). The main source of labour statistics are labour force surveys (LFS), which are designed with the specific goal of measuring labour market and employment indicators. The second-most prevalent source of data in ILOSTAT is "other household surveys", many of which are multi-topic living conditions surveys such as those implemented by or modelled after the World Bank's Living Standards Measurement Study (LSMS) programme.

While ILO sets international standards and produces guidance for the collection of labour statistics which facilitates international harmonization, LFS are not standardized internationally, and this may result in limited comparability. Moreover, not all LFS are detailed and well-designed enough to measure all key concepts of interest properly. While LFS are regularly implemented in data-rich countries (annually or even quarterly), their frequency in low-income countries is irregular: several of the lower-middle and low-income countries included in ILOSTAT appear to have conducted only one LFS since 2010.

Many low- and middle-income countries use multi-topic living conditions surveys and household income and expenditure surveys (HIES) to monitor key development outcomes, including poverty. Active since the early 1980s, the Living Standards Measurement Study (LSMS) programme[8] has produced over 100 surveys. While the LSMS surveys generally provide fewer employment indicators than LFS, these integrated multi-topic household surveys make it possible to link employment to other important features such as poverty, health, shocks and agriculture. LSMS and HIEStype surveys are ideally conducted every three to five years, but an assessment undertaken in the context of poverty monitoring efforts revealed that 77 low- and middle-income countries have failed to run two or more poverty surveys every 10 years, with 57 of them having either zero or just one poverty data point between 2002 and 2011 (Serajuddin et al., 2015).

The World Bank has been implementing the LSMS-ISA (Integrated Surveys on Agriculture) programme in eight African countries since 2009. Given this programme's agricultural focus, it is of particular relevance for the analysis of rural development issues. The panel nature of the LSMS-ISA surveys, with individuals being tracked across survey rounds, offers the advantage of making it possible to monitor education, skills and employment over time, even when individuals migrate to other areas within the same country. These surveys can therefore contribute to a better understanding of the process of transitioning from school to work and across different types of employment status. In addition, as the LSMS-ISA surveys are georeferenced, they also offer the potential for integration with other data sources, such as sources of administrative and remote sensing data.

8 http://surveys.worldbank.org/lsms/programs/integrated-surveys-agriculture-ISA.

The ILO School-to-Work Transition Survey (SWTS) is designed to address some of the challenges associated with employment transitions by collecting information concerning the labour market situation of young people between the ages of 15 and 29 as they exit school.[9] The survey is supplemented by a second component – a survey of employers – that aims to provide information on the features of the demand for young workers (Elder, 2009). By running these two components simultaneously, the SWTS captures mismatches in the supply and demand for young workers that obstruct school-to-work transitions. The SWTS is not intended, however, to generate youth employment indicators such as labour force participation rates, unemployment and underemployment rates, or employment-to-population ratios, which are provided by LFS data (Elder, 2009).

Other potential vehicles for gathering the same type of information on the changing nature of the demand for labour are enterprise and establishment surveys. The country coverage and periodicity of these types of surveys are, however, far from complete, and the informal sector often remains largely, if not completely, outside of the scope of the enumeration. Increasing survey coverage, expanding the range of information of relevance for rural youth and enhancing the scope for integration with household and labour surveys are clearly priorities for the future development of these instruments from a rural youth employment policy perspective.

International and regional student assessment programmes started measuring learning outcomes in the 1960s, with increasing standardization and harmonization coming in the 1990s and 2000s (Altinok, Angrist and Patrinos, 2018). The two largest such programmes are the Programme for International Student Assessment (PISA), covering 71 countries in 2015, and the Trends in International Mathematics and Science Study (TIMSS), covering 65 countries in 2015. While few developing countries participate in these large assessment programmes, there are several regional student assessment programmes in developing countries, notably the Latin American Laboratory for Assessment of the Quality of Education (LLECE) run by the United Nations Educational, Scientific and Cultural Organization (UNESCO) in Latin America, the Southern and Eastern African Consortium for Monitoring Educational Quality (SACMEQ) and the Programme for the Analysis of the Education Systems of CONFEMEN [Conférence des ministres de l'Éducation des États et gouvernements de la Francophonie] member countries (PASEC) in sub-Saharan Africa (Altinok, Angrist and Patrinos, 2018).

A recent effort by UNESCO and the World Bank has harmonized many international and regional student assessment databases, creating the Harmonized Learning Outcomes database, which contains comparable data on 163 countries, 32 of which are in SSA, for the last 50 years (Altinok, Angrist and Patrinos, 2018). The education component of the World Bank's Human Capital Index is based on this database.

The Organisation for Economic Co-operation and Development (OECD) coordinates the Survey of Adult Skills, which has been conducted in over 40 countries as part of the Programme for the International Assessment of Adult Competencies (PIAAC). The survey measures "the key cognitive and workplace skills needed for individuals to participate in society and for economies to prosper." It covers adults between the ages of 16 and 65 and assesses literacy and numeracy skills and problem-solving ability. It also collects information on how skills are used at work and in other contexts.[10]

The World Bank's Skills Toward Employability and Productivity (STEP) is a survey-based skill measurement programme. It covers the working-age (15-64) urban population in 13 low- and middle-income countries and has in-depth modules on cognitive, non-cognitive and technical skills. This programme measures cognitive skills on the basis of both self-reporting and the administration of a short reading comprehension test and contains the Big Five, the "grit" measure, and time and risk preferences for non-cognitive skills. The programme also includes an accompanying employer survey that enables it to gauge both labour supply and demand (Pierre at al., 2014).

The Young Lives survey series follows two cohorts composed of 12,000 children and youths between the ages of 1 and 22 in a longitudinal study spanning a period of 15 years (2002-2017) in urban and rural areas of Ethiopia, India, Viet Nam and Peru. It administers a more elaborate set of tests to measure cognitive skills and has an ample non-cognitive skills module, though it does not cover the Big Five. Both the STEP and Young Lives surveys also have detailed labour modules covering many of the key labour market indicators discussed in section 2.

9 https://www.ilo.org/employment/areas/youth-employment/work-for-youth/WCMS_191853/lang--en/index.htm.

10 http://www.oecd.org/skills/piaac/.

Data and measurement challenges

While the availability of data on low-income countries, in general, and on youth, employment and skills, in particular, has improved over the years, considerable challenges remain that limit our understanding of the challenges facing rural youth. Some of these constraints are linked to conceptual and methodological issues that make accurate measurement challenging, while others are simply related to shortages of the human and financial resources that would be required in order for national statistical programmes in many countries to be able to produce even basic information on a regular basis. This section summarizes some of the priority areas for action in these domains.

Defining "employment". In accordance with the most recent international definition, work must be performed for pay or profit in order for it to be classified as "employment" (19th ICLS, resolution I, para. 27). This definition is a challenging one to apply in rural contexts, as determining whether agricultural work should be classified as employment depends on whether the work outputs are used for profit. To implement this definition in household and labour force surveys, the boundary between use for profit and own use, which is often blurred in agriculture, is drawn on the basis of the intended use of the outputs. However, preliminary results from ongoing World Bank research suggest that a significant share of surveyed farmers do not use their outputs as originally intended. Determining employment status based on intended output use may thus leave respondents misclassified and lead to inaccuracies in labour statistics. The classification is also sensitive to the choice of the threshold of output used for profit. Further methodological work will determine best practices for implementing the new standard and its effect on estimates of the labour force and employed population.

Data availability. Data on skills and employment are scarce in developing countries, in general, and in rural areas in such countries, in particular. One of the major skills-focused survey programmes, STEP, covers only urban areas. The coverage of student assessment databases is still overwhelmingly confined to developed countries. Individual-level employment data are also limited in developing countries, particularly in SSA (Headey, Bezemer and Hazell, 2010; Szirmai et al., 2013; World Bank, 2012, p. 34). ILO, for instance, reports that 37 per cent of all year/country observations of labour force participation for 1990-2017 are based on actual data, rather than simulations, such as LFS, censuses or – in some cases – official government estimates (ILO, 2017b). In SSA, only 8.4 per cent of year/country data points are based on real observations, however, as most developing countries do not conduct LFS on a regular basis. Similarly, an ILO review shows that 160 out of the 236 countries and territories worldwide implemented an LFS between 2000 and 2010 (ILO, 2013a). Expanding the coverage and frequency of high-quality household and labour force surveys is imperative for an informed dialogue and the adoption of effective policy decisions.

Data integration. Non-traditional data sources, such as social media profiles, professional profiles or online behaviour, have the potential to supplement household surveys and aid in filling some of the existing gaps. There is also scope for increasing the integration of traditional data sources (censuses; household, labour and establishment surveys; administrative data) and the integration between these sources and non-traditional data sources. Integration can add value to each individual data source by expanding the range of possible uses. In the case of household, labour and establishment surveys, their combined use can, for instance, yield more insights into mismatches between labour demand and labour supply. Using social media and other sources of big data for public policy formulation often requires some degree of validation and model training for which traditional data sources are a key input. While integration is an attractive proposition, making it a reality at scale will require a concerted effort to address both methodological and privacy concerns.

Use of proxy respondents. The potential impact on data quality of the use of proxy respondents in individual-level microdata collection exercises is an issue that has received limited attention. The overwhelming majority of household survey operations in low- and middle-income countries still either do not identify their respondents or make extensive use of proxy respondents.

Given what is currently known about the impact of proxy reporting on individual-level data on a range of topics, the level of reliance on proxy respondents is a potential source of concern, even for a household survey programme that has achieved remarkable success on many fronts since 2009. Kilic and Moylan (2016) uncover distortionary, intra-household proxy respondent effects on individual-level measurements of asset ownership in the context of a methodological survey experiment in Uganda. The authors find that a non-ignorable share of female and male respondents classifying themselves as being *without* reported ownership, economic ownership or specific rights could in fact be tagged as owners or rights holders by other respondents in the same household. Dammert and Galdo (2013) and Janzen (2018) report significant effects of the use of proxy respondents on child labour estimations in Peru and the United Republic of Tanzania, respectively, while Dillon et al. (2012) find strong effects for questionnaire design (screening questions) but no significant effects for the use of proxy respondents on child labour statistics in a survey experiment in the United Republic of Tanzania.[11] Analysing data from Malawi and Nigeria, Palacios-Lopez, Christiaensen and Kilic (2017) find opposite effects for respondent gender on reported female adult (aged 15+) labour share in crop production in Malawi (7 percentage points higher if the respondent is female) and Nigeria (lower but not significant).

While a more systematic approach to methodological research appears to be necessary in order to study the (age- and gender-differentiated) impact of proxy reporting on individual-level data collection on a range of topics, including labour and skills, in a diverse set of geographies, a new initiative, known as the Living Standards Measurement Survey – Plus (LSMS+), is assisting selected IDA (International Development Association) borrowing countries on a pilot basis to absorb the additional cost[12] of collecting intra-household, individual-level household survey data on asset ownership, employment and entrepreneurship without using proxy respondents. The LSMS+ is, as a start, working towards providing support to six such countries under the IDA18 (2017-2020) window.

Measuring non-cognitive skills. Instruments for measuring non-cognitive skills, in particular the Big Five, have been validated with highly educated people in developed countries. Recent work in rural Kenya has found, however, that these instruments suffer from a serious degree of measurement error, suggesting that the non-cognitive skills measures developed to date may not be suitable for developing-country and rural contexts (Laajaj and Macours, 2017). Laajaj et al. (2018) use data on 50,000 individuals collected as part of the STEP surveys to show that measurement issues persist in the wider developing-country context. These recent findings highlight the need for further methodological research into how to best capture and measure non-cognitive skills in developing countries.

Measuring farm work. ILO definitions and recommendations for the collection of key labour statistics are not always straightforward when attempts are made to apply them to rural developing-country contexts, where a large part of the population is engaged in agricultural labour, often on the family farm (Arthi et al., 2018). These difficulties arise from the nature of family farm work, which tends to be seasonal and irregular. Because of this irregularity, survey labour modules, which usually enumerate "hours worked in the past seven days" or "hours usually worked" in a given activity, are ill-equipped to adequately capture important employment indicators, such as hours worked (Arthi et al., 2018). An improved way of measuring farm labour, following Reardon and Glewwe (2000), which is employed, for example, in LSMS-ISA surveys, is by enumerating farm work in more detail as part of a dedicated agricultural module. In these surveys, respondents are asked to recall the number of hours they worked on each of the household's plots during the last agricultural season. However, as Arthi et al. (2018) and Gaddis et al. (2018) show, this method suffers from recall bias, as respondents tend to overestimate the number of hours worked during the agricultural season, and from listing bias, as respondents fail to report all the plots under cultivation. Regular (e.g. weekly) enumeration of farm work can rectify these biases, but visiting households so regularly is costly. Arthi et al. (2018) and Gaddis et al. (2018) explore the possibility of substituting phone calls for in-person visits, with promising initial results.

11 For the same dataset, Bardasi et al. (2011) find strong effects for the questionnaire design on male labour participation in agriculture and for the use of proxy respondents on male employment rates, while Serneels, Beegle and Dillon (2016) also find strong effects for questionnaire design but not for proxy respondents on returns to education.

12 The additional cost could be up to 31 per cent per household, according to the estimates provided by Kilic and Moylan (2016). The added amount principally covers the additional time spent in each sampled enumeration area for a given survey in order to accommodate respondent availability to take part in personal interviews.

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