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A Tale of Two Countries: Labor Market Profiles of Youth in Urban and Rural Cameroon

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A Tale of Two Countries: Labor Market Profiles of Youth in Urban and Rural Cameroon

Ioana Botea and Mitja Del Bono[1]

Abstract

Cameroon's high employment levels mask widespread precariousness and rural-urban inequality. Labor market vulnerability—either detachment or weak attachment—is particularly acute among youth (ages 15 to 35), who are often uninterested in agriculture yet unable to access better opportunities in urban areas. Using Latent Class Analysis (LCA), a non-parametric method that segments a heterogeneous population into groups sharing similar characteristics, we identify distinct profiles of youth experiencing labor market vulnerability. The largest groups in urban and rural areas consist of mostly men with some education who work full time in the informal sector, either as own-account workers or subsistence farmers. In addition, we identify five groups as priorities for policy intervention. First, two groups making up 9 percent of out-of-school youth, predominantly married women, are involuntarily inactive and present an opportunity for improved human capital utilization. Second, a third group (14 percent) includes women in rural areas employed as contributing family workers, while two other groups (12 percent) comprise women facing multifold vulnerabilities (i.e., a combination of unpaid, temporary, and part-time work). Tailored interventions for these three groups would most impact poverty reduction.

JEL codes: J13, J16, J21, J24, J46

Keywords: labor market vulnerability, youth employment, informality, gender

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1 Introduction

As typical in the Africa region, vulnerable and low-productivity employment rather than absolute employment levels is the main labor market challenge in Cameroon. High labor force participation (74 percent) and low unemployment (4 percent) rates mask the fact that own-account and household work is prevalent among those who are employed.[2] Despite improvements in education and skills, the vast majority of the labor force (90 percent) is employed in the informal sector, mainly low-skill, low-earnings jobs that lack access to social protection services. While the government has made reducing underemployment – or working in jobs where skills are not adequately utilized– a main policy objective,[3] available data suggests a persistent upwards trend instead. Moreover, labor market indicators vary substantially across socio-demographic characteristics. Youth, women, and those with low education are especially disadvantaged, with important differences between rural and urban areas.

Young Cameroonians (ages 15 to 35) are more likely than older adults to be inactive, unemployed, or underemployed. Out-of-school youth in Cameroon are twice as likely as non-youth to be out of the labor force (19 percent vs. 10 percent), with even higher rates among young women. For youth in the labor force, unemployment is more common than for the general population and especially so among urban youth with higher education (20 percent). Youth who are employed tend to be relegated to low-skill informal sector jobs characterized by insecurity, seasonality, and low earnings. Having attained considerably higher education levels than previous generations, youth struggle to find work outside their families' farms or to access better (salaried) employment opportunities in urban areas.

This paper contributes to existing research by employing Latent Class Analysis (LCA) to identify different youth profiles and inform tailored policy responses. Using LCA, the paper identifies empirically-derived typologies of youth in Cameroon and provides a nuanced and actionable understanding of their labor market challenges. In addition to grouping youth based on labor market vulnerabilities (e.g., temporary or unpaid employment), it describes their dominant socio-demographic characteristics to inform potential targeting approaches. Given the nature of the data, the analysis focuses on supply-side constraints and corresponding policies. To our knowledge, the present study is the first of its kind in Africa,[4] demonstrating the appropriateness of the technique in a highly informal labor market.

The study consists of five sections including this introduction. Section 2 provides summary statistics on the Cameroonian labor market and its stark rural-urban divide. Section 3 describes the framework and the statistical clustering methodology. Section 4 presents the results, including a description of the identified clusters according to labor market vulnerability indicators and corresponding demographic and socio-economic characteristics. Finally, section 5 presents conclusions along with policy recommendations. Unless otherwise stated, all statistics presented in the paper are Authors' calculationss based on the 2014 Fourth Cameroon Household Survey (*Quatrième Enquête Camerounaise Auprès des Ménages*, ECAM4).

[2] Unless otherwise stated, all statictics are based on the 2014 Fourth Cameroon Household Survey (*Quatrième Enquête Camerounaise Auprès des Ménages*, ECAM4).
[3] The 2010-2020 *Document de Stratégies pour la Croissance et l'Emploi* (DSCE) aimed to reduce the underemployment rate from 76 percent to under 50 percent by 2020. The objective to drastically reduce underemployment is repeated in the 2020-2030 *Stratégie Nationale de Développement (SND30*).
[4] Similar analyses were carried out in upper middle-income contexts such as Turkey, Croatia, Poland, Greece, and Romania (Ferré, Immervoll, & Sinnott, 2013; Immervoll, 2013; Sundaram et al., 2014).

2 The Cameroonian Labor Market

2.1 Labor Market Overview

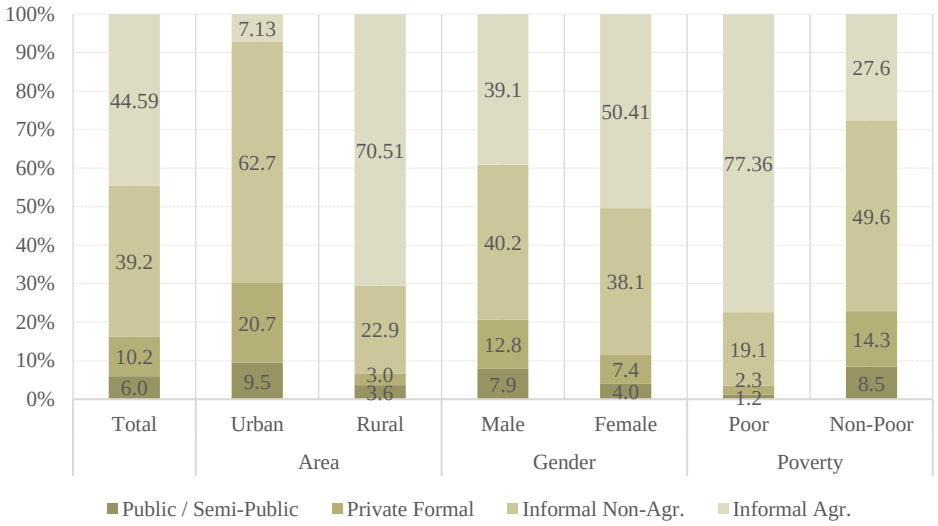
Poverty and inequality are increasing in Cameroon due to unequal growth, rapid demographic change, and conflict. Several years of robust economic growth have had an insufficient impact on the poverty rate, which was estimated at 38 percent in 2014 compared to 40 percent in both 2001 and 2007. Moreover, due to rapid population growth, the number of people living in poverty has increased substantially over the past two decades, especially in the fragile North and Far North regions which account for 56 percent of the poor. In addition to worsening regional inequality, the gap between rural and urban areas is also widening: while the poverty rate decreased substantially in urban areas (from 18 percent in 2001 to 9 percent in 2014), it increased in rural areas (from 52 percent in 2001 to 57 percent in 2014). The ongoing Anglophone crisis in North-West and South-West regions has severely harmed the local economy, further exacerbating poverty and causing massive internal displacement.

Cameroon has low human capital development and utilization rates. Despite vast natural resources and a relatively well-educated workforce, Cameroon has a Human Capital Index (HCI) of 0.40, meaning that a child born in Cameroon today will be 40 percent as productive when s/he grows up as s/he could be if s/he enjoyed complete education and full health. This score is below both Sub-Saharan African and lower-middle-income country averages. Given the limited opportunities to utilize accumulated human capital in adulthood, the HCI drops to 0.28 when considering the fraction of the working-age population that is employed (basic utilization of HCI). The HCI drops to 0.23 when adjusted for the mismatch between skills and cognitive abilities required to do a job (full utilization of HCI). In other words, less than 1 in 4 Cameroonian children will be able to meet their potential and access high-productivity work in adulthood.

Rapid demographic growth and urbanization further highlight the need for better employment opportunities. Between 2010 and 2018, Cameroon's population increased by 4.7 million and is projected to continue to expand due to the high fertility rates (4.5 births per woman). As a result, 70 percent of the population is under 30 years, and youth between the ages of 15 and 35 make up 66 percent of the working-age population. Moreover, Cameroon has one of the highest rates of urbanization in Sub-Saharan Africa, with 56 percent of the population living in urban areas in 2019, compared to 44 percent in 2000. The United Nations forecasts that by 2050, 70 percent of Cameroon's population is going to live in urban areas. While offering an opportunity to generate a demographic dividend, Cameroon's increasingly young and urban population also risks exacerbating poverty and causing social unrest if not provided with adequate jobs.

The Cameroonian labor market is predominantly informal. Almost 90 percent of the labor force works in the informal sector: 45 percent of the labor force works in informal agriculture and 39 percent in informal non-agriculture (see *Figure 1* below). Informality is prevalent in urban as well as rural areas (70 percent and 93 percent, respectively) and for men as well as for women (79 percent and 89 percent, respectively). Virtually all poor Cameroonians (97 percent) earn their living in the informal sector. The formal sector employs 16 percent of the labor force, mainly men in urban areas, with the public sector representing a smaller share than the private sector (6 percent versus 10 percent). Yet private sector development in Cameroon is hampered by a series of challenges, including a weak business environment and a mismatch between generalist skills at university (mainly for the public sector) and skills demanded by the market (Sosale and Majgaard, 2016).

Figure 1. **Employment by sector (in percentages)**



Source: Authors' calculations using ECAM4 (2014).

Low productivity in the informal sector is, therefore, the main labor market challenge in Cameroon. As typical in the region, absolute employment levels are not a major concern in Cameroon. Labor force participation is high (74 percent), and although women are significantly less likely to be in the labor force compared to men (almost 10 percentage points lower), the female labor force participation figure in Cameroon remains above the Sub-Saharan African average (69 percent versus 61 percent). Only 4 percent of the labor force are unemployed and only 1 percent among the poor, underscoring that most active Cameroonians cannot afford to not work. Low-pay precarious work in the informal sector is however prevalent: as such, a majority of those employed (58 percent) earn less than the national minimum wage of CFAF 36,270 per month (US$63 equivalent).[5] Among the employed poor, 33 percent are unpaid. In addition, one-third (28 percent) of those employed work fewer than 40 hours a week (time-related underemployment).

Employment in Cameroon mainly takes the form of self-employment, either as own-account workers or contributing family members. At the national level, three-quarters (72.5 percent) of workers are self-employed, with 57.2 percent working on their own account (see *Figure 2* below). Another 15 percent work as contributing family members, with rates twice as high among women than men (22 percent versus 9 percent). Only 21 percent of Cameroonians are in wage employment, which tends to provide higher and more stable earnings, and 3 percent work as apprentices or with other working arrangements. The poor are almost exclusively self-employed (91 percent), either as own-account workers (64 percent) or typically unpaid family help (28 percent). Lacking productive job opportunities and unable to afford to be unemployed, most Cameroonians, therefore, work for themselves or other family members, with limited prospects of generating enough earnings to lift themselves out of poverty.

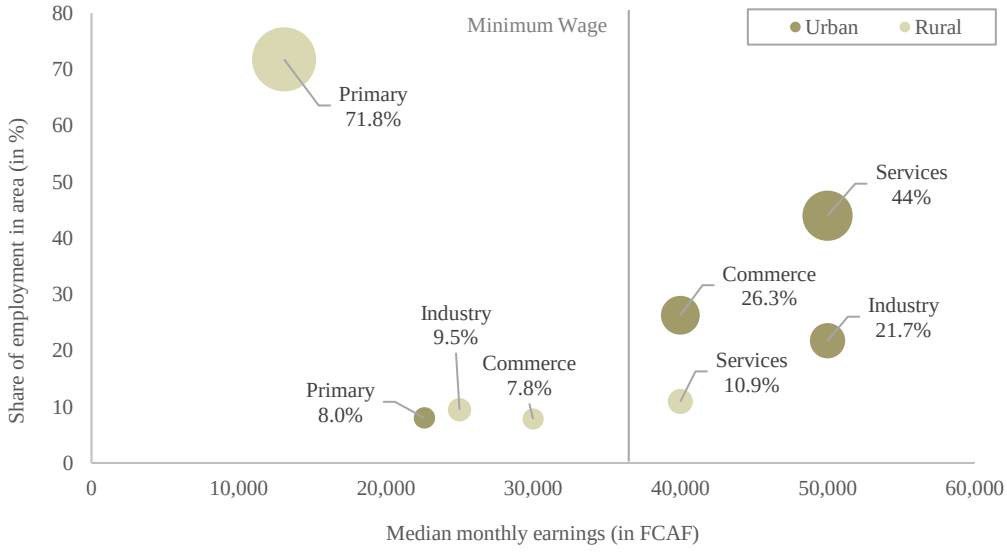
[5] Annual earnings for a minimum-wage worker would be US$804, compared to a per capita poverty line of US$550 (CFAF 339,715).

Figure 2. **Employment status (in percentages)**

Source: Authors' calculations using ECAM4 (2014).

The Cameroonian labor market is further characterized by important rural-urban differences. As shown in *Figure 3* below, approximately 90 percent of rural workers earn less than minimum wage compared to 10 percent of urban workers. There is a marked rural concentration (~70 percent of rural employment) in the low-skilled, low-paid primary sector, while more lucrative service sector jobs (wages up to five times higher than primary sector jobs) are concentrated in urban areas. This points to two very different economies and labor markets: while rural areas remain focused on subsistence agriculture, urban areas are increasingly modernizing and diversifying. Indeed, according to a 2018 report, cities in Cameroon are at least 1.8 times more productive than rural areas (World Bank, 2018). While cities' tradable sectors are important for generating better quality jobs, it's critical at least in the short term to improve productivity and expand employment opportunities in the rural areas where a majority of Cameroonians (especially the poorest and most in need of assistance) continue to reside.

Figure 3. **Productivity estimates, by area of residence and employment sector**



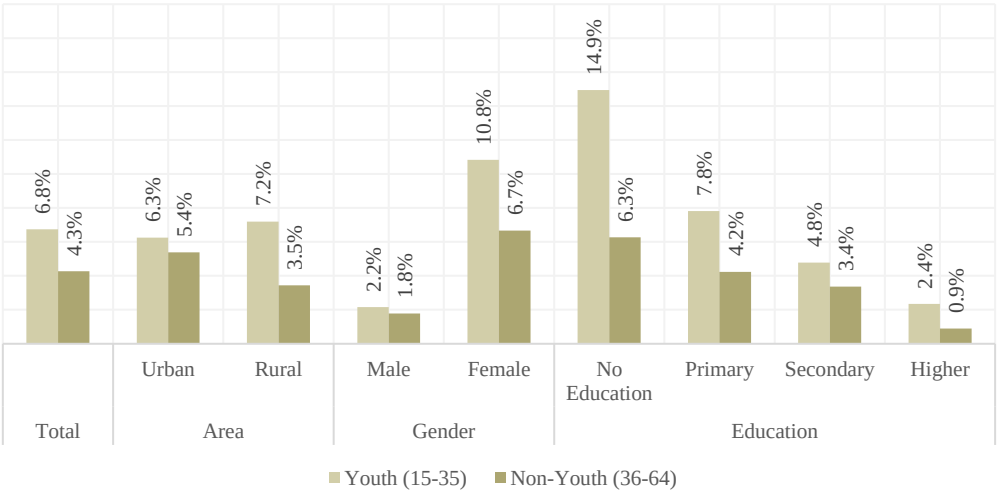
Source: Authors' calculations using ECAM4 (2014).

2.2 Youth-Specific Vulnerabilities

The Cameroonian workforce is young, with 59 percent of workers aged between 15 and 35.[6] Given the rapid population growth over the past couple of decades, youth comprise 66 percent of the population in Cameroon. A third (29 percent) of youth are still in school, while 14 percent are economically inactive. Around half of youth (57 percent) are in the labor market, including 3 percent who are unemployed. As explored in more detail in the rest of the paper, labor market exclusion and vulnerability are particularly acute among young Cameroonians, who tend to have highereducationaln attainment and aspirations than their parents but persistently limited access to adequate employment opportunities.[7]

Youth are twice as likely to be inactive than non-youth (20 percent vs. 10 percent), either involuntarily or voluntarily. Among youth, as shown in *Figures 4 and 5* below, the widest gaps are along gender and education lines. First, inactivity rates are more than double for young women than young men (25 percent vs. 11 percent), primarily driven by involuntary inactivity. The main reasons reported include a perceived lack of job opportunities or the required qualifications when these exist, refusal of the spouse, or respect of tradition. Second, there's a strong correlation between education and the likelihood of being inactive, however it, goes in opposite directions for voluntary or involuntary inactivity. Comparing the two ends of the spectrum, those with no education are much more likely to be out of the labor force involuntarily than those with higher education (15 percent vs. 2 percent), while the opposite is true when looking at those who exit the labor force by choice (19 percent vs. 9 percent). The high rates of voluntary inactivity are particularly striking when compared with those among non-youth, which hover at 5-6 percent regardless of education level.

***Figure 4*. Rate of involuntary inactivity, by age group**

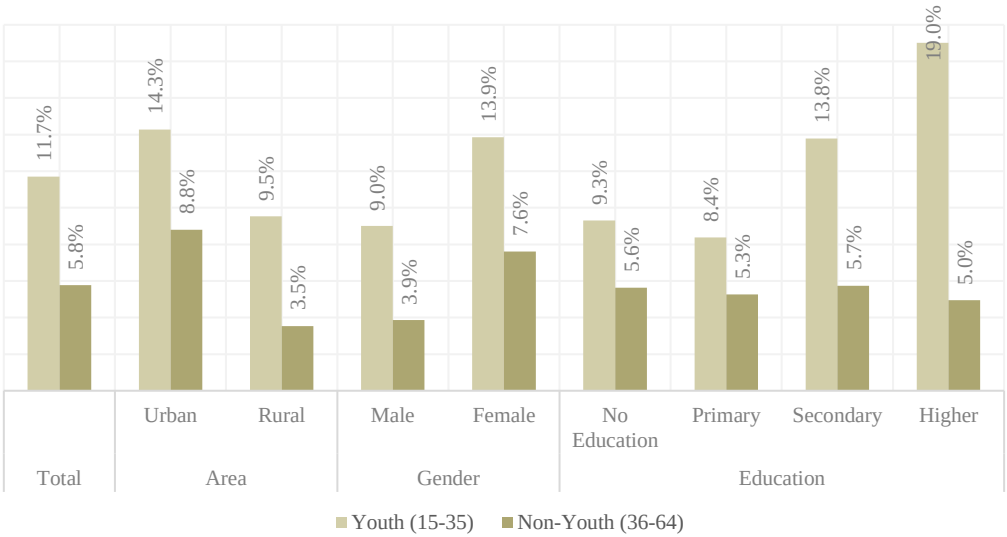


Source: Authors' calculations using ECAM4 (2014).

[6] The 15-35 age range to define youth is the range used by the African Union and adopted by the Government of Cameroon in official documents.

[7] We recognize that there is a "life cycle" of employment, with low participation, then informality, then (some) formality, and then self-employment (Dhillon and Yousef, 2009; Peeters et al., 2009; Cunningham and Salvagno, 2011). In addition, the Oaxaca decompositions for adults relative to youth often find high returns to experience and much lower returns to education. In other words, being in the labor force, acquiring practical human capital, assets (physical capital), and connections (social capital) have been shown to have substantially more value than human capital. Disparities between youth and non-youth are thus, to a certain extent, part of a natural evolution of the workforce as individuals gain experience and build assets and social capital.

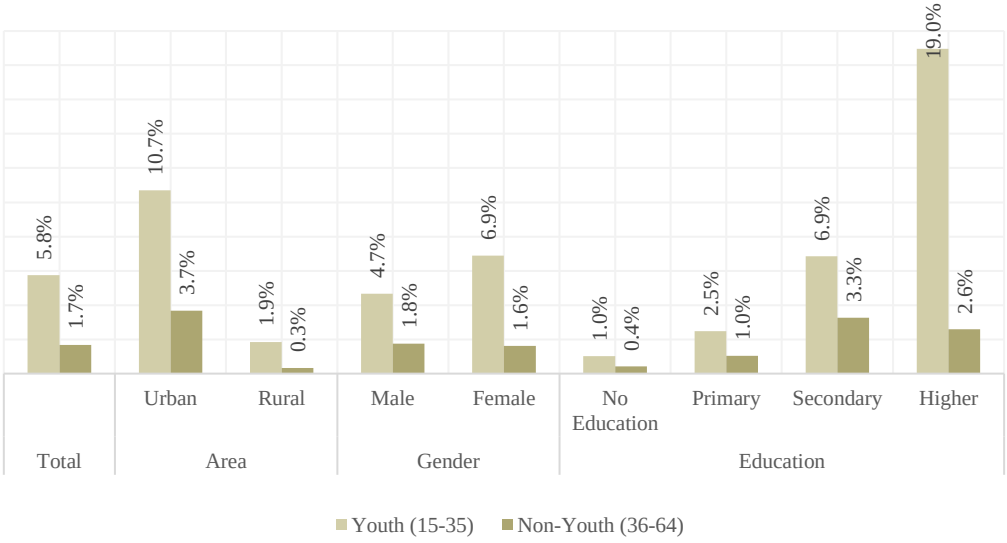
***Figure 5*. Rate of voluntary inactivity, by age group**



Source: Authors' calculations using ECAM4 (2014).

For economically active youth, unemployment is on the rise, particularly in urban areas and among those with higher education. The youth unemployment rate has been steadily increasing over the past decade, from 4.6 percent in 2007 to 6.3 percent in 2014, likely reflecting the increased urbanization rate.[8] As shown in *Figure 6* below, overall unemployment is three times higher for youth compared to non-youth (6 percent vs. 2 percent), and this pattern holds across socio-demographic characteristics. The issue is particularly salient among those with higher education (19 percent vs. 3 percent) and in urban areas (11 percent vs. 2 percent). The unemployment rate among urban youth with university degrees is 20 percent, compared to 3 percent among non-youth with the same characteristics. Most unemployed youth are typically holding out for public sector jobs given the associated high salaries and job security. Limited job creation in the private sector as well as the mismatch between the generalist skills typically acquired in university and those demanded by the private sector further restrict employment options.

***Figure 6*. Unemployment rate, by age group**

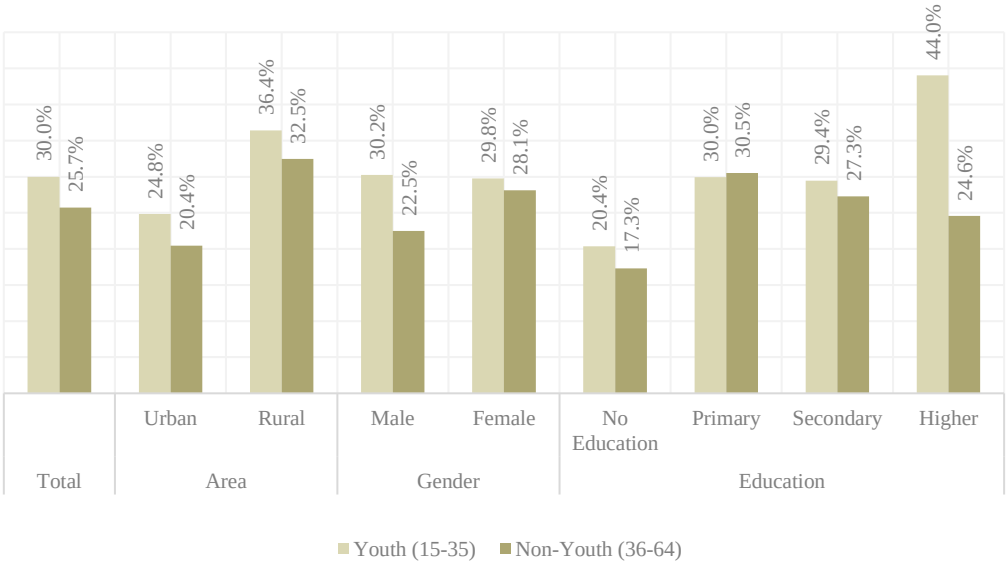


Source: Authors' calculations using ECAM4 (2014).

[8] 2007 was the first year in which youth unemployment started increasing after a stable decrease in the previous years (youth unemployment was 11% in 2001).

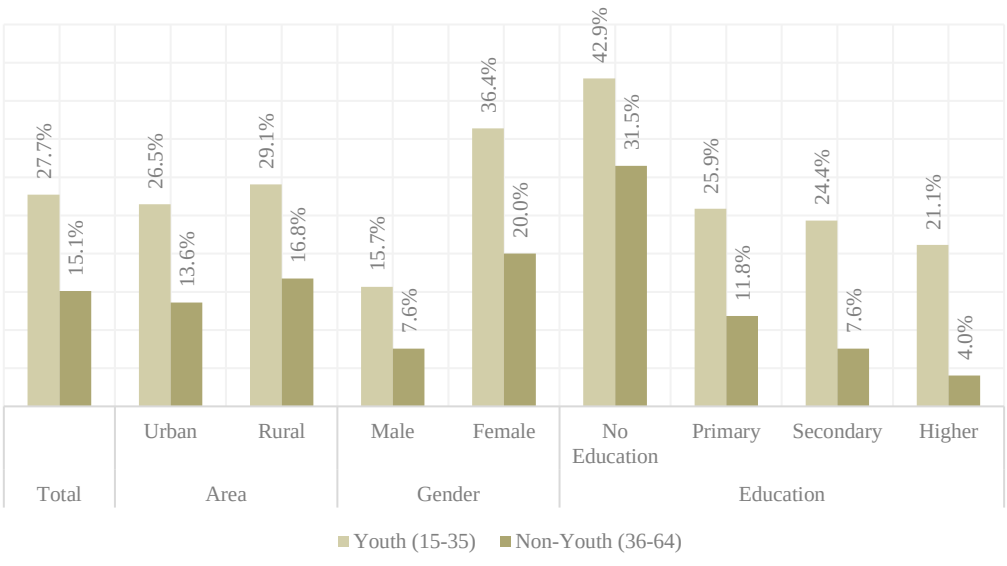
Almost a third of young workers are time-related underemployed, working fewer than 40 hours per week. While still higher among youth than non-youth, the gap in terms of time-related underemployment is narrower than for other indicators. A notable exception is, again, among those with higher education: youth with university degrees are almost twice as likely as comparable non-youth to be time-related underemployed (44 percent vs. 25 percent). An even clearer gap emerges in terms of temporary employment (i.e., working less than a third of the calendar year), which is twice as common among youth than non-youth (28 percent vs. 15 percent). As shown in *Figure 8*, youth with no education (43 percent) and young women (35 percent) are most likely to work for limited periods. While more likely to be inactive or unemployed than other youth in general, when they're employed, youth with higher education are the least likely to work temporarily (4 percent).

Figure 7. **Rate of time-related underemployment, by age group**



Source: Authors' calculations using ECAM4 (2014).

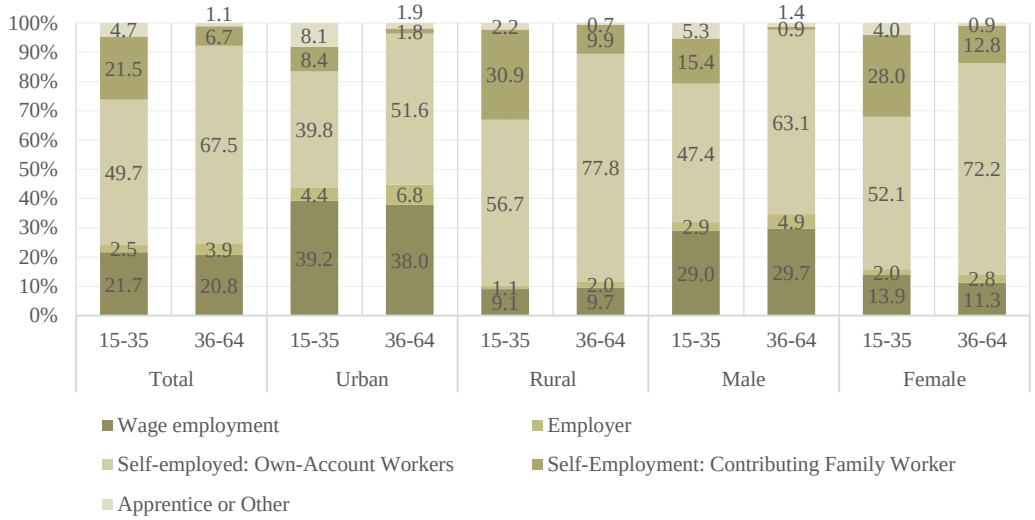
Figure 8. **Rate of temporary employment, by age group**



Source: Authors' calculations using ECAM4 (2014).

Low-pay employment is equally common, with a high share of youth engaged in unpaid work. Two-thirds of youth (60 percent) earn less than the minimum wage, compared to 56 percent of non-youth. On average, youth earn 40 percent less than their older counterparts. The differences are driven by sector of activity: public sector jobs, which are typically held by non-youth, pay twice as much as formal private sector jobs and four times as much as the informal sector. Largely excluded from the public sector, youth are relegated to lower-paying sectors and activities within those sectors. As shown in *Figure 9* below, the relatively high share of youth employed as contributing family workers (22 percent vs. 7 percent) further explains the pay gap. Employment that takes the form of household aid is especially common for youth in rural areas (31 percent) and among women aged 15 to 35 (28 percent).

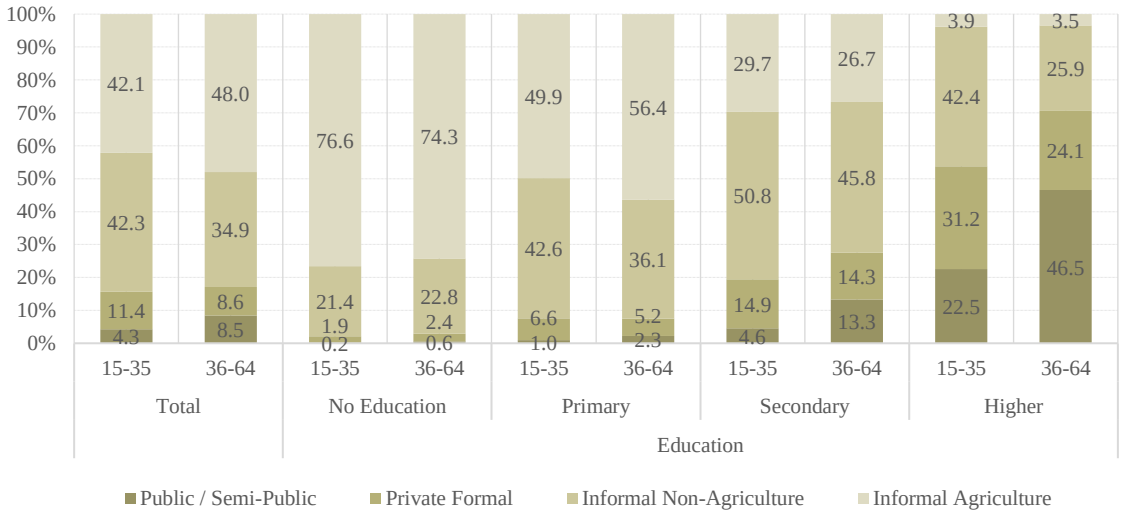
***Figure 9*. Employment status, by age group**



Source: Authors' calculations using ECAM4 (2014).

Finally, widespread informality underlies all aspects of labor market vulnerability presented above. Similar shares of youth and non-youth work in the informal sector (84 percent vs. 83 percent). As *Figure 10* illustrates, significant differences between youth and non-youth emerge only among those with higher education (46 percent vs 29 percent), driven by low access to public sector jobs among youth.

***Figure 10*. Rate of informality, by age group**



Source: Authors' calculation using ECAM4 (2014).

3 Youth Profiles: Methodology

The remainder of the study deepens the analysis of labor market vulnerability among youth to (i) identify groups experiencing similar challenges in the labor market, and (ii) describe the socio-demographic characteristics, or "profile", these groups. In contrast to the previous section presenting one labor market aspect disaggregated by one socio-demographic dimension at a time, this section discusses the overlapping vulnerabilities and characteristics that exist in practice in toform tailored employment support interventions.

3.1 Data and Reference Population

As the descriptive analysis in Section 2, the LCA relies on the most recent nationally-representative household survey. The Fourth Cameroon Household Survey (*Quatrième Enquête Camerounaise Auprès des Ménages*, ECAM4) was conducted by the National Insitute of Statistics in 2014. The survey is part of the government's effort to regularly measure living conditions indicators and to monitor progress towards the national development and growth strategy. As the name suggests, ECAM4 is the fourth of its kind, following previous waves in 1996, 2001, and 2007. It was conducted on a sample of 12,897 households across 1,024 clusters nationwide.

The reference population – the focus of the current analysis – comprises youth aged 15 to 35 who are out of school. It represents a subset of the Cameroonian population of working age, i.e.,15 through 64 years old, and includes both: (i) youth who are inactive, thus experience "detachment" from the labor market, and (ii) youth who are unemployed or experiencing a range of vulnerabilities (e.g., low-pay, working less than 40 hours/week) and, therefore, have a "weak-attachment" to the labor market. As shown in *Table 1*, the reference population represents 5,399,576 individuals, or 71 percent of youth and 25 percent of the entire Cameroonian population.

Reflecting the substantial labor market differences in rural and urban areas previously documented, separate analyses are conducted by the place of residence. The reference population is split almost evenly between rural and urban areas (2,921,778 vs. 2,477,798 individuals) despite an overall majority of the population living in rural areas. This is because the urban population is substantially younger than the rural population (youth make up 41 percent vs. 30 percent) due to the relatively higher rates of migration among young people seeking education and employment opportunities in towns and cities.

Table 1. **Reference population, national and by region (population in thousand, share in %)**

	Samples					
	National		**Urban**		**Rural**	
Category	**Pop.**	**Share**	**Pop.**	**Share**	**Pop.**	**Share**
Total	21,770,519		8,806,211		12,964,308	
Working age (15-64)	11,411,622		5,250,420		6,161,202	
Youth (15-35)	7,580,589	100.00	3,630,549	100.00	3,950,041	100.00
In school	2,181,014	28.77	1,152,751	31.75	1,028,263	26.03
Reference Pop.	5,399,576	71.23	2,477,798	68.25	2,921,778	73.97
Employed	4,078,332	53.80	1,733,598	47.75	2,344,734	59.36
Unemployed	224,119	2.96	185,039	5.10	39,080	0.99
Inactive	1,097,125	14.47	559,161	15.40	537,964	13.62

Source: Authors' calculations using ECAM4 (2014).

3.2 Labor Market Vulnerability Indicators

The descriptive analysis (in Section 2) identified *seven* main labor market vulnerability indicators among out-of-school youth in Cameroon. As discussed above, these indicators indicate either detachment from or weak attachment to the labor market. The weak-attachment indicators can overlap (e.g., those working informally will typically also have a higher risk of being unpaid), illustrating the overall productivity and security challenges associated with this type of jobs. To ensure consistency across indicators, or "characteristics", and simplify the analysis, all used indicators are binary.

Three indicators are used for labor market detachment:

1. **Involuntary inactivity (INI)**: individuals not working or not seeking work because there is no employment, do not think they can obtain employment without qualification, do not know how to seek employment, face refusal from the spouse, other involuntary reasons;
2. **Voluntary inactivity (VOI)**: individuals not working or not seeking work because they're waiting to start a new job, do not need/want to work, do not consider themselves of working age, or for other voluntary reasons;
3. **Unemployment (UNE)**: individuals not working but seeking employment opportunities.

Four indicators are used for weak attachment to the labor market:

4. **Time-related underemployment (TRU)**: individuals working less than 40 hours a week, also referred to as "visible underemployment";
5. **Temporary employment (TEM)**: individuals working less than a third of the calendar year, typically employed by the day or to work on specific, time-bound tasks;
6. **Unpaid employment (UNP)**: workers not remunerated for their economic activities;
7. **Informal sector employment (INF)**: individuals working for enterprises that are not formally registered or without a contract.

Table 2. **Statistics by indicator, national, and by region (% given of reference population)**

	Samples					
	National		**Urban**		**Rural**	
Category	**Pop.**	**Share**	**Pop.**	**Share**	**Pop.**	**Share**
Reference Pop.	5,399,576		2,477,798		2,921,778	
None	461,400	8.55	372,377	15.03	89,022	3.05
INI	464,805	8.61	205,250	8.28	259,556	8.88
VOI	632,320	11.71	353,911	14.28	278,408	9.53
UNE	224,119	4.15	185,039	7.47	39,080	1.34
TRU	554,847	10.28	248,964	10.05	305,882	10.47
UNP	843,467	15.62	137,989	5.57	705,478	24.15
INF	3,396,699	62.91	1,193,925	48.18	2,202,774	75.39
TEM	551,627	10.22	322,420	13.01	229,206	7.84

Source: Authors' calculations using ECAM4 (2014).

As shown in *Table 2*, weak-attachment characteristics are more common than detachment characteristics. Informal employment is by far the most widespread characteristic, as it represents 63 percent of the national reference population (48 percent urban vs. 75 percent rural).[9] Unpaid employment is also frequent, especially in rural areas where 24 percent of youth are

[9] A social security variable was included in the initially tested methodology given its relevance to the study of labor-market vulnerabilities, yet it was highly correlated to the informality variable and was therefore discarded.

unpaid. Among detachment characteristics, voluntary inactivity is the most common and especially so in urban areas (14 percent vs. 10 percent). Only 8.6 percent of the reference population don't experience any labor market vulnerability as defined by detachment and weak-attachment indicators.

3.3 Methodology

Latent Class Analysis (LCA), a statistical clustering method, is used to identify sub-groups of youth with similar patterns of labor market vulnerability. The methodology enables the characterization of a categorical latent, or unobserved, variable (in this case, labor market vulnerability) by analyzing the relationship between several observed variables (i.e., the indicators or characteristics, as defined above). It allows the statistical segmentation of the reference population into groups based on the likelihood that individuals share similar characteristics. In contrast to traditional regression analyses, which identify the effect of one indicator while assuming all the other indicators stay constant, LCA exploits the interrelations of the various characteristics to generate real-life vulnerability profiles.

Once groups of youth sharing similar labor market challenges are identified, the approach generates socio-demographic profiles to inform policy response. Segmenting the population into groups experiencing different degrees of labor market vulnerability is important for prioritizing employment support policies and programs in the likely event that resources are limited. Moreover, linking specific labor market challenges with socio-demographic profiles can inform the design of tailored interventions that address well-identified and data-driven constraints. Different youth are likely to need different forms of support, with adaptations likely to improve both impacts on employment outcomes and the cost-effectiveness of government investments.

The LCA has multiple advantages relative to other clustering or segmentation techniques. First, the use of statistical tests and critical values guide the choice of the optimal number of clusters as well as the parametrization of the model for optimizing its fitting to the data. Second, the LCA provides probabilities of membership to groups rather than direct determination, which reduces the potential classification error and biased estimation. And third, it deals more easily with common survey issues, such as missing data or complex measurements and can allow the inclusion of different scaling and variable types (Fernandez et al., 2016).

The technique requires a study of the optimal number of clusters that best represents the reference population and its respective observed attributes. It begins by testing the use of labor market attributes as predictors of class membership to a multinomial latent variable. This is done by incrementing the number of classes from two classes to 12 classes while goodness-of-fit statistics are assessed across the models. These statistics include the G2, the log-likelihood statistics, the Akake Information Criterion (AIC), the Bayes Information Criterion (BIC), and the degrees of freedom (Nylund, Asparouhov, & Muthen, 2007). For the present analysis, a model including six classes was selected for the urban sample and a model including seven classes was selected for the rural sample. See *Annex 1* for a comparison of goodness-of-fit statistics across the models tested and the selection of the number of classes adopted.

BOX 1. A Short Introduction to Latent Class Analysis (LCA)[10]

Let us consider three broad binary labor market vulnerability characteristics: **1) underemployment, 2) informality, and 3) lack of social security**. Each indicator takes the value of 1 when the worker faces the specifici type of vulnerability and 0 otherwise. With a sample of *N* individuals, the *response pattern* depends on the values taken by the four items (Table B1). Given the presence of 3 indicators and 2 possible values for each indicator, the **number of possible response patterns** is 2x2x2 = 8.

Table B1. Response pattern of labor-market vulnerability characteristics

Individual ID	Under-employment	Informality	Lack of Social Security	Response Pattern
1	1	1	0	101
2	1	1	0	100
3	0	1	1	011
4	0	0	1	001

The Latent Class Analysis (LCA) is used for searching the most frequent and similar response patterns among the data and group them intoto homogeneous clusters (or classes). For instance, in the above example, individuals 1 and 2 are both underemployed and informally employed. Therefore, a frequent response pattern could be y = (11.), where the dot represea nts *lack of social security* and leaves open the possibility for further heterogeneity among the entire target population.

For instance, if the LCA algorithm finds the most frequent response patterns among the sample to be y1 = (1,1,0) and y2 = (0,1,0), it would identify the existence of two latent classes, one for each of the most frequent response patterns. Then, workers with different response patterns would be allocated to either class 1 or class 2, but with different probabilities, depending on the overlap between the responses.

The model is then restricted to "mechanically" have either detachment or weak-attachment classes since the former have exclusive attributes (i.e., no overlapping is allowed). This restriction increases the parsimony and stability of the specification (Vermunt & Magidson, 2005) and is validated by re-assessing goodness-of-fit statistics (e.g., log-likelihood, AIC,, and BIC). We recognize that including detachment features in the LCA model is not needed given that they don't overlap with other characteristics (e.g., an individual is either involuntarily inactive or unemployed and cannot at the same time be in unpaid employment or work in the informal sector). The choice to, nevertheless, present detachment features alonwith g weak-attachment features aims to provide a comprehensive and consistent analysis of labor market vulnerabilities in Cameroon.

The LCA model is finalized by adding active covariates to the previous specification and by validating its predictive power. The introduction of covariates which have a significant effect on class-membership probabilities can further reduce misclassification errors and improve the predictive power of the model (Wurpts & Geiser, 2014). Based on their relevance for program targeting, used covariates include sex, age group,, and education level. The model including the active covariates is once again validated by goodness-of-fit statistics. Furthermore, the misclassification error is estimated by cross-classifying the modal assignment (i.e., allocation based othe n the highest posterior probability) with the probability-based assignment (Vermunt & Magidson, 2005). The misclassification error stands as a measure of predictive effectiveness for the specification and is here found to be lower than 30 percent, the threshold above which a

[10] Adapted from Fernandez et al. (2016).

specification is significantly not able to discriminate between classes (Fernandez et. al, 2016). Finally, the bivariate residuals (BVR) are computed for assessing whether the observed association between two variables is well reproduced by thewhether modewhether l and the local independence assumption holds as valid. Most of the bivariate residuals computed (see *Annex 1 Table 5* and *Table 6*) are found to be not concerning as below the significance value of 3.84.

Once the complete model is finalized, the resulting probabilities of class membership are used for predicting the classes of the sample. The designation is in turn used for the characterization, which is undertaken by computing two-way statistics summarizing the relationship between the group membership of the sample and the respective socio-economic characteristics. The latter are arbitrarily chosen and based on the knowledge of covariates deemed as suitable for understanding intra-cluster dynamics and beneficial for policy-making purposes. The individual features adopted for the characterization are broadly represented by groups of indicators (e.g., human capital or employment) which can respectively describe the socio-demographic and employment profile of the classes.

4 Youth Profiles: Results

4.1 Urban Results

In the urban sample, the reference population is segmented into *six* distinct classes of varying sizes by the LCA. The model finds *three* labor market detachment classes and *three* weak-attachment classes, accounting for 30 and 70 percent of the reference population, respectively. The detachment classes have no overlapping characteristics as their attributes are exclusive: an individual is either involuntarily inactive, voluntarily inactive, or unemployed.[11] The weak-attachment classes, on the other hand, may share the same characteristics but with different incidences or probabilities, depending on the combination of labor market vulnerabilities experienced by different groups of employed youth. *Table 3* below shows the size of each group (or class) along with the associated likelihood of experiencing each characteristic.

Table 3. **Detachment and Weak-Attachment Classes in Urban Areas**

	Detachment Classes			Weak-Attachment Classes		
Class-membership	**1**	**2**	**3**	**4**	**5**	**6**
Population Share	13.97	8.23	7.42	35.09	19.44	15.85
Population Size	346,187	203,869	183,867	869,566	481,695	392,613
Incidence of Characteristics (in %)						
INI	0.00	100.00	0.00	0.00	0.00	0.00
VOI	100.00	0.00	0.00	0.00	0.00	0.00
UNE	0.00	0.00	100.00	0.00	0.00	0.00
TRU	0.00	0.00	0.00	6.66	24.73	15.76
UNP	0.00	0.00	0.00	1.29	25.63	0.25
INF	0.00	0.00	0.00	82.50	85.95	23.28
TEM	0.00	0.00	0.00	8.43	34.24	15.61

Source: Authors' calculations using ECAM4 (2014).

[11] The LCA doesn't, therefore, add value to the identification of detachment classes. We present the results for both detachment and weak-attachment classes in this format for consistency and ease of interpretation.

The largest of the six identified groups, comprising a third of the urban reference population (35 percent), includes informal workers unlikely to experience other types of labor market vulvulnerabilityndividuals in Group 4 have an 83 percent probability of being informal sector workers, 8 percent to be in temporary employment, and 7 percent to be in time-related underemployment. The second largest group (Group 5), accounting for 19 percent of urban youth, appears to be the most vulnerable: not only are individuals in this group even more likely ththanhose in Group 4 to be informal sector workers, but they're also substantially more likely to experience a range of other vulnerabilities, including being unpaid and in either/both time-related underemployment or temporary employment. Finally, the third largest and last weak-attachment group (Group 6), accounting for 16 percent of urban youth, includes those experiencing a positive but relatively lower level of vulnerability.

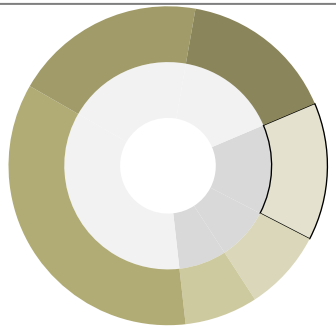
The three detachment groups include the remaining third of out-of-school urban youth, most of whom are outside the labor force. Unlike the weak-attachment classes which reflected a combination of characteristics, the detachment classes are characterized by single, mutually exclusive, characteristics. Most of the urban youth who are out of work are involuntarily inactive (14 percent, Group 1), followed by those who are voluntarily inactive (8 percent, Group 2), and the unemployed (7 percent, Group 3). These figures emphasize the importance of going beyond traditional measures of youth marginalization to account for those who are either discouraged or prevented from looking for employment and who, combined, represent 1 in 5 out-of-school youth in urban areas.

The boxes below provide short descriptions of each of the six groups, including associated demographic and socio-economic characteristics. The groups have been named according to their most salient out-of-sample characteristics (i.e., the features adopted for describing the classes identified by applying the LCA model to the in-sample characteristics). The profiles below present the mix of labor market vulnerabilities faced by each group as well as socio-demographic characteristics. See *Annex 2* for more detailed results.

The Urban Detachment and Weak-Attachment Classes

***Group 1*: Well-Educated, Unmarried Women Who Are Voluntarily Inactive**

Demography	69% female, mainly (40%) between 25-29 years old, largely single (60 percent)
Human Capital	75% with secondary/higher education, 50% with vocational training or apprenticeships, and 50% without any working experience
Geography	37% in Yaoundé and 31% in Douala
Wealth and Income	8% in poverty, 67% without savings

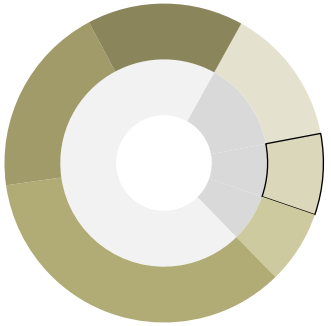


Class Size
13.97% of the reference pop.
346,187 individuals

Labor-Market Attributes
Voluntary Inactive 100%

***Group 2*: Poor, Low-Skilled, Married Women Who Are Involuntarily Inactive**
(over-represented among Muslim households in the Far North region)

Demography	86% female, 32% between 20-24 years old, 32% between 25-29 years old, 63% married and largely Muslim (41%)
Human Capital	55% with no or with primary education, 31% with vocational training or apprenticeships, and 52% without any working experience
Geography	24% in Douala, 20% in Yaoundé, and 17% in the Far-North
Wealth and Income	10% in poverty, 74% without savings

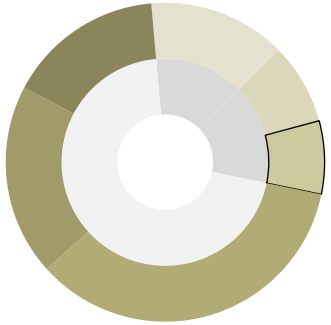


Class Size
8.23% of the reference pop.
203,869 individuals

Labor-Market Attributes
Involuntary Inactive 100%

***Group 3*: Well-Educated, Single Women Who Are Unemployed**

Demography	64% female, 70% older than 25 years, 66% single
Human Capital	84% with secondary or higher education, 60% with vocational training or apprenticeships, 27% without any experience, and 41% with more than 10 years of experience
Geography	43% in Yaoundé and 36% in Douala
Wealth and Income	5% in poverty, 65% without savings

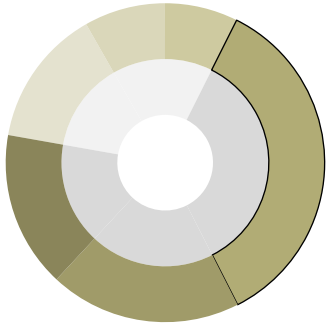


Class Size
7.42% of the reference pop.
183,867 individuals

Labor-Market Attributes
Unemployment 100%

***Group 4*: Educated, Older Men Who Work in the Informal Sector**

Demography	66% male, 30% in small households of 1-2 members, 82% older than 25 years old
Human Capital	92% with primary and secondary education, 60% with vocational training or apprenticeships, 58% with more than 10 years of experience
Geography	34% in Douala and 29% in Yaoundé
Employment	56% self-employed and 20% qualified employees, 83% in private non-ag enterprises,and 42% worked since younger than 15 years
Wealth and Income	7% in poverty, 63% without saving

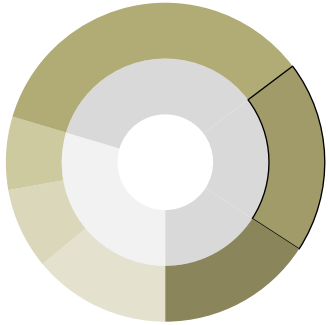


Class Size
35.09% of the reference pop.
869,566 individuals

Labor-Market Attributes
Informality 82.50%

***Group 5*: Young, Single Women Who are Employed but Experiencing Most Vulnerability**

Demography	64% female, 31% in households larger than 7, 52% younger than 25, 61% single
Human Capital	66% with secondary and higher education, 61% with vocational training or apprenticeships
Geography	32% in Yaoundé and 31% in Douala
Employment	44% own-account workers, 33% contributing family workers, 41% in services, in private enterprises, and 44% worked since younger than 15
Wealth and Income	9% in poverty, 62% without savings

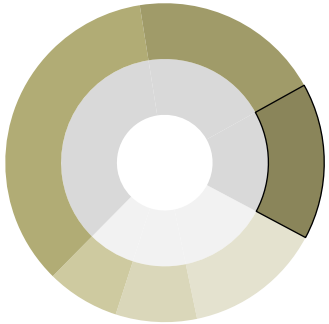


Class Size
19.44% of the reference pop.
481,695 individuals

Labor-Market Attributes
Informality 85.95%
Temporary Employment 34.24%
Unpaid Employment 25.62%
Time-Related Underemployment 24.73%

***Group 6*: Older, Well-Educated Men With Lower Vulnerability**

Demography	57% male, 31% in small (1-2 members) households, 60% are 30-35 years old and 34%ares 25-29 years old, 49% married
Human Capital	55% with higher education, 45% with secondary education, 79% with vocational training or apprenticeships, 66% with more than 10 years of experience
Geography	36% in Yaounde and 39% in Douala
Employment	54% qualified employees and 20% managers, 67% in services, 18% in the administration,and 32% in private formal enterprises.
Wealth and Income	2% in poverty, 49% without savings



Class Size
15.85% of the reference pop.
392,613 individuals

Labor-Market Attributes
Informality 23.28%
Time-Related Underemployment 15.76%
Temporary Employment 15.61%

4.2 Rural Results

In the rural sample, the reference population is segmented into *seven* distinct classes by the LCA. The model identifies *three* detachment classes and *four* weak-attachment classes, accounting for 20 and 80 percent of the out-of-school youth, respectively. As with the urban sample, the detachment classes are standalone in terms of vulnerability characteristics, while the weak-attachment classes combine different characteristics at varying probabilities. *Table 4* below shows the size of each group (or class) along with the associated likelihood of experiencing each characteristic.

***Table 4*. Detachment and Weak-Attachment Classes in Rural Areas**

	Detachment Classes			Weak-Attachment Classes			
Class-membership	**1**	**2**	**3**	**4**	**5**	**6**	**7**
Population Share	9.43	8.86	1.34	44.57	25.58	5.66	4.57
Population Size	275,569	258,765	39,080	1,302,201	747,418	165,236	133,510
Incidence of Characteristics (in %)							
INI	0.00	100.00	0.00	0.00	0.00	0.00	0.00
VOI	100.00	0.00	0.00	0.00	0.00	0.00	0.00
UNE	0.00	0.00	100.00	0.00	0.00	0.00	0.00
TRU	0.00	0.00	0.00	14.61	5.75	29.24	13.41
UNP	0.00	0.00	0.00	2.55	61.07	42.49	0.79
INF	0.00	0.00	0.00	100.00	100.00	91.91	13.55
TEM	0.00	0.00	0.00	7.62	3.01	34.37	15.85

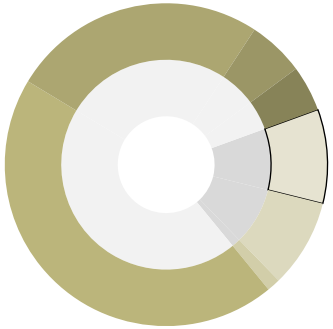
Source: Authors' calculations using ECAM4 (2014).

The largest of the seven identified groups (Group 4), accounting for almost half (45 percent) of all out-of-school rural youth, includes paid informal sector workers who are somewhat likely to be in time-related underemployment. The second largest group (26 percent, Group 5) includes informal sector workers with a high likelihood of being unpaid. Far smaller groups experience either multifold labor market vulnerability (6 percent, Group 6) or little vulnerability (5 percent, Group 7). A smaller share of the rural sample is detached from the labor market, compared to the urban sample, with virtually all those who are out of work being inactive. Only 1 percent (Group 3) of out-of-school youth in rural areas are unemployed. If out of the labor force, there's an equal chance that rural youth are either voluntarily inactive (9 percent, Group 1) or involuntarily inactive (9 percent, Group 2). More detailed descriptions of each group are presented in the boxes below, and the full results can be found in *Annex 2*.

The Rural Detachment and Weak-Attachment Classes

Group 1: Unmarried Women with Some Education Who Are Voluntarily Inactive

Demography 64% female, 88% between 15-29 years old, 62% single
Human Capital 61% without or with primary education, 23% with vocational training or apprenticeships, 69% without any working experience
Geography 24% in Far-North, 17% in North-West, 14% in Center
Wealth and Income 46% in poverty, 77% without savings

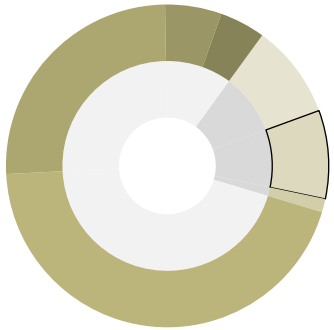


Class Size
9.43% of the reference pop.
275,569 individuals

Labor-Market Attributes
Voluntary Inactive 100%

Group 2: Uneducated, Married Women Who Are Involuntarily Inactive

Demography 87% female, equally distributed ages, 65% married, 51% Muslim
Human Capital 43% without education, 14% with vocational training or apprenticeships, 71% without any working experience
Geography 20% in Adamaoua, 17% in Far-North, 13% in Center
Wealth and Income 49% in poverty, 85% without savings

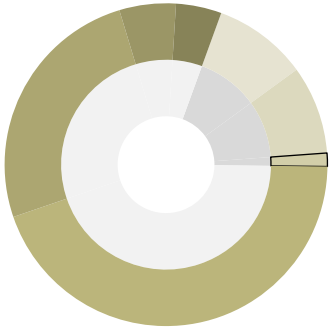


Class Size
8.86% of the reference pop.
258,765 individuals

Labor-Market Attributes
Involuntary Inactive 100%

Group 3: Individuals with Some Education and Some Experience Who Are Unemployed

Demography	55% female, 78% between 20-29 years old, 54% married, and largely Protestant (36%)
Human Capital	50% with secondary and 39% with primary education, 49% with vocational training or apprenticeships, 36% without any working experience
Geography	22% in Center, 21% in North-West, 15% in Adamaoua
Wealth and Income	30% in poverty, 75% without savings

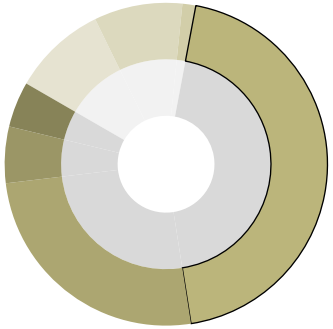


Class Size
1.34% of the reference pop.
39,080 individuals

Labor-Market Attributes
Unemployment 100%

Group 4: Married Individuals Engaged in Subsistence Agriculture

Demography	47% female, 80% between 25-35 years old, 72% married
Human Capital	26% without education, 26% with vocational training or apprenticeships, 80% with more than 10 years of experience
Geography	21% in Far-North, 20% in North, 12 in North-West
Employment	89% self-employed, 62% in agriculture and informal, 56% worked since younger than 15
Wealth and Income	49% in poverty, 82% without savings

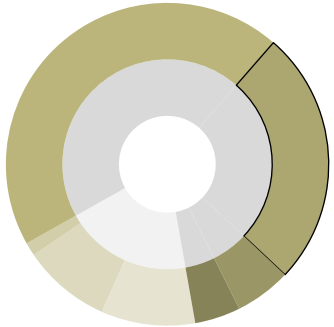


Class Size
44.57% of the reference pop.
1,302,201 individuals

Labor-Market Attributes
Informality 100%
Time-Related Underemployment 14.61%

***Group 5*: Poor, Married Women with Limited Education Who Are Unpaid Family Workers**
(mainly in the North and Far North regions)

Demography	73% women, 45% in households with more than 7 members, ages equally distributed, 60% married, large share of Muslim (34%)
Human Capital	50% without education, 39% with primary education, 14% with vocational training or apprenticeships, with more than 2 years of experience
Geography	44% in Far-North, 22% in North
Employment	66% contributing family workers, 32% self-employed, 85% in agriculture and informal, 68% worked since younger than 15
Wealth and Income	68% in poverty, 87% without savings

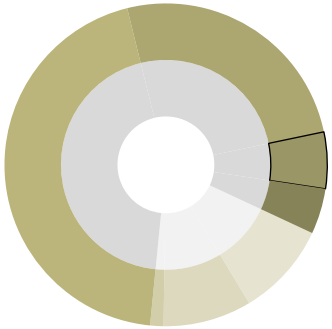


Class Size
25.58% of the reference pop.
747,418 individuals

Labor-Market Attributes
Informality 100%
Unpaid Employment 61%

***Group 6*: Unmarried Women with Some Education Experiencing Multifold Vulnerability**
(mainly in the Far North and Anglophone regions)

Demography	60% women, 43% in households with more than 7 members, 52% aged 15-19 and 29% aged 20-24, 61% single
Human Capital	41% with primary and 49% with secondary education, 34% with vocational training or apprenticeships, with more than 2 years of experience
Geography	22% in Far-North, 19% in North-West, 14% in South-West
Employment	55% contributing family workers, 35% self-employed, 54% in the primary sector, 37%the in non-agricultural-informal-private sector, 61% worked since younger than 15
Wealth and Income	45% in poverty, 79% without savings

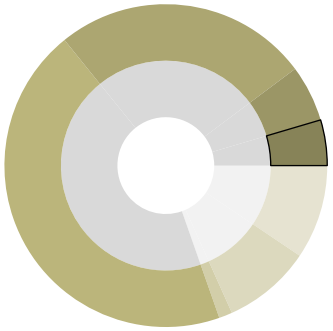


Class Size
5.66% of the reference pop.
165,236 individuals

Labor-Market Attributes
Informality 91.90%
Unpaid Employment 42.50%
Temporary Employment 34.80%
Time-Related Underemployment 29.20%

***Group 7*: Well-Educated, Married Men with Low Vulnerability**

Demography	32% female, 79% in households with less than 7 members, 34% aged 25-29 and 58% aged 30-35, 62% married, largely Protestant (37%)
Human Capital	33% with higher education, 45% with secondary education, 76% with vocational training or apprenticeships, with more than 2 years of experience
Geography	18% in North-West, 14% in South-West
Employment	82% qualified employees, 24% managers, 18% laborers, 70% in services, 47% in public administration, 16 % in private and formal
Wealth and Income	19% in poverty, 61% without savings



Class Size
4.57 of the reference pop.
133,510 individuals

Labor-Market Attributes
Temporary Employment 15.80%
Informality 13.50%
Time-Related Underemployment 13.40%

4.3 Priority Classes

Five groups emerge as priorities based on the extent of their labor market vulnerability and poverty rates. This includes two detachment groups – Group 2 Urban (*Poor, Low-Skilled, Married Women Who Are Involuntarily Inactive*) and Group 2 Rural (*Uneducated, Married Women Who Are Involuntarily Inactive*), and three weak attachment groups – Group 5 Urban (*Young, Single Women Who are Employed but Experiencing Most Vulnerability*), Group 5 Rural (*Poor, Married Women with Limited Education Who Are Unpaid Family Workers)*, and Group 6 Rural (*Unmarried Women with Some Education Experiencing Multifold Vulnerability*). Women comprise the majority, ranging from 60 percent to 87 percent, of all priority groups. Social protection interventions may further prioritize the poorest and most vulnerable groups (i.e., the three weak-attachment groups experiencing the highest incidence of poverty), while active labor market interventions may further prioritize the groups with the most potential for improved human capital utilization (i.e., the two detached groups). Different groups should be prioritized depending on the specific policy or program objective, which in turn should be tailored to the specific needs of the group targeted.

Both priority detachment groups predominantly include married women who are involuntarily inactive. The two groups of involuntarily inactive youth make up 8-9 percent of both the urban and rural sub-samples, or 462,364 individuals in total, and have the highest shares of women among all groups (86 percent, urban; 87 percent, rural). Compared to voluntarily inactive individuals (Group 1 Urban and Group 1 Rural), those not engaging in the labor market involuntarily are substantially more likely to be married (63 percent vs. 39 percent, urban; 65 percent vs. 35 percent, rural) and have lower educational levels (45 percent attained secondary or higher education vs. 75 percent, urban; 22 percent vs. 39 percent, rural). In addition, involuntarily inactive groups are more likely to be Muslim (41 percent vs. 15 percent, urban; 51 percent vs. 31 percent, rural). These differences point to underlying social norms limiting women's schooling and work outside the home. Active labor market interventions should, therefore, aim to address these constraints in addition to more standard interventions such as skills development or the provision of productive inputs.

The three priority weak-attachment groups include youth who typically work in the informal sector and face a variety of labor market vulnerabilities. Taken together, Group 5 Urban, Group 5 Rural, and Group 6 Rural, comprise 51 percent of the youth workforce, or 1,394,349 individuals. They differ from Group 4 Urban and Group 4 Rural (see below) along two key socio-demographic lines: they're majority women (64 percent vs. 34 percent for the urban groups, and 73 percent vs. 47 percent for the rural groups, on average) and substantially younger (52 percent under 25 vs. 18 percent, urban; and 58 percent vs. 20 percent, rural). The consequences in terms of labor market vulnerability are significant: while comparably likely to work in the informal sector (86 percent vs. 84 percent, urban; and 100 percent, rural), the younger, majority-women groups are also often unpaid (26 percent vs. 5 percent, urban; and 61 percent vs. 0 percent, rural) and/or employed as family aid workers (33 percent, urban; 66 percent, rural). Partly explained by the age difference, with some vulnerability characteristics likely to lessen or disappear as young women gain more experience, the gender gap remains nevertheless notable.

Otherwise, the largest groups in the urban and rural sub-samples comprise relatively older youth who work in the informal sector. Taken together, Group 4 Urban (*Educated, Older Men Who Work in the Informal Sector*) and Group 4 Rural (*Married Individuals Engaged in Subsistence Agriculture*), add up to 40 percent of the youth workforce, or 2,171,767 individuals. The groups experience a similar pattern of labor market vulnerability: the majority are employed in the informal sector (83 percent for the urban group and 100 percent for the rural group), with relatively low chances of being time-related underemployed (7 percent, urban; 15 percent, rural) or temporarily employed (9 percent, urban; 8 percent, rural). Both groups also consist of older youth: more than 80 percent are aged over 25 (82 percent, urban; 80 percent, rural) and almost half are aged over 30 (45 percent, urban; 47 percent, rural).

The remaining detachment groups highlight the increasingly concerning issue of labor market detachment, especially among well-educated youth in urban areas. Group 1 Urban (*Well-Educated, Unmarried Women Who Are Voluntarily Inactive*) and Group 3 Urban (*Well-Educated, Single Women Who Are Unemployed)* include 21 percent of the urban sub-sampl, or 530,054 individuals. Although the two groups are distinct in terms of labor market status – Group 1 includes those voluntarily inactive and Group 3 the unemployed – they are remarkably similar in terms of socio-economic characteristics. Both groups are two-thirds women (69 percent, inactive; 64 percent, unemployed) and unmarried (60 percent, inactive; 66 percent, unemployed). About half of the individuals in either group have secondary or higher education (75 percent, inactive; 84 percent, unemployed) but no working experience (49 percent, inactive; 52 percent, unemployed). Somewhat similarly, Group 1 Rural (*Unmarried Women with Some Education Who Are Voluntarily Inactive*) mainly includes unmarried women under age 29 who are voluntarily inactive. Compared to their counterparts in urban areas, however, individuals in Group 1 Rural tend to have lower education attainment (61 percent attended only primary school) and higher poverty rates (46 percent vs. 8 percent).

Finally, the three remaining groups are the least likely to require support through labor market interventions. Group 3 Rural (*Individuals with Some Education and Some Experience Who Are Unemployed*) includes a negligible share of the population (1 percent). Group 6 Urban (*Older, Well-Educated Men With Low Vulnerability*) and Group 7 Rural (*Well-Educated, Married Men with Low Vulnerability*) are also not prioritized because they include well-educated, older youth who experience little to no labor market vulnerability.

5 Conclusions and Recommendations

Out-of-school Cameroonian youth, who comprise two-thirds of the workforce, are disadvantaged in the labor market relative to older workers. Youth (ages 15 to 35) are twice as likely as non-youth to be outside the labor force (20 percent vs. 10 percent), with particularly high inactivity rates among young women (27 percent). In addition, unemployment is three times higher among youth than non-youth (6 percent vs. 2 percent), reaching 20 percent among urban youth with university degrees. When employed, young workers are more likely to be temporarily employed (28 percent vs. 15 percent among non-youth) or unpaid (22 percent vs. 6 percent among non-youth). Unpaid employment, in the form of household aid or apprentice, is especially

common for youth in rural areas (31 percent) and among women (29 percent). While these differences are partly explained by a natural work progression as youth gain experience and build social and productive capital, the increasingly competitive labor market highlights the need for targeted employment support.

"Youth" is a heterogeneous population with distinct labor market challenges and socio-demographic characteristics. Using Latent Class Analysis, we identify *six* youth profiles in urban areas and *seven* profiles in rural areas. In urban areas, a third of youth (35 percent, Group 4), mainly men, work in the informal sector without experiencing other vulnerability characteristics. Women typically face a range of other vulnerabilities, such as unpaid or temporary employment, in addition to informality (19 percent, Group 5). They also make up the majority of all three groups detached from the labor market, tending to be involuntarily inactive (8 percent, Group 2) if they're married and either unemployed (7 percent, Group 3) or discouraged (14 percent, Group 1) if they're unmarried. Only 16 percent (Group 6) of all Cameroonian youth living in urban areas, mainly older youth with higher education, don't experience any labor market vulnerability. In rural areas, almost half (45 percent, Group 4) of youth are engaged in subsistence agriculture. Another quarter of rural youth (26 percent, Group 5) are women working as unpaid family support. Women are, again, overrepresented among inactive youth, split evenly along marital status between voluntary (9 percent, Group 1) and involuntary (9 percent, Group 2) inactivity. Unemployment is virtually nonexistent in rural areas (1 percent, Group 3), and only 5 percent of youth (Group 7) experience no or low labor market vulnerability.

The stark differences between rural and urban areas require different policy and programmatic responses. Low productivity, associated with the continued predominance of household farming, is particularly salient in rural areas. To improve productivity as well as make agriculture more attractive to youth and curb the pace of urbanization, interventions should provide young people with the resources (e.g., business skills, grants, and support structures) to build sustainable micro-enterprises producing, transforming, or trading agricultural products. This type of intervention would primarily benefit the 10 percent of youth who are voluntarily inactive or unemployed (Groups 1 and 3) and the 45 percent engaged in subsistence agriculture (Group 4). Conversely, urban areas are confronted with rising unemployment in addition to persistent informality and low productivity. While a growing share of youth are completing secondary and higher education, the demand for formal sector jobs far exceeds the supply. Based on the analysis, skills development and micro-entrepreneurship support interventions in urban areas would primarily benefit youth who are either inactive or unemployed (21 percent, Groups 1 and 3) as well as those engaged in low-skills, low-pay jobs in the informal sector (35 percent, Group 4).

In addition to addressing specific labor market vulnerabilities, employment promotion interventions should be tailored to the profile of the target population. Not all youth comprising one of the groups identified based on labor market challenges share the same set of socio-demographic characteristics. For instance, Group 5 Rural includes married women who work and will likely continue to work as unpaid family aid as well as typically younger, unmarried men and women who are currently unpaid because they work as apprentices but are likely to start earning money soon. Addressing the labor market challenge of unpaid work, therefore, requires a granular understanding of and adaptations to the often quite different backgrounds and constraints.

Finally, a gender lens should be applied across employment promotion policies and programs. The analysis unambiguously shows that young women face higher labor market vulnerability than young men across indicators. If married, women have a high likelihood of being economically inactive (Group 2 Urban and Group 2 Rural) and, if unmarried, they tend to work either as unpaid family support or in the most precarious forms of employment (Group 5 Urban and Groups 5 and 6 Rural). The identified gender gaps emphasize the need for complementary interventions (e.g., engaging gatekeepers such as husbands or community leaders) to promote social norms change and encourage women's economic participation. Supporting women's productive employment through gender-responsive measures is important not just to improve their autonomy and living standards, but also to slow down demographic growth, improve children's outcomes, and reduce the intergenerational transmission of poverty.

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Annex 1. Latent Class Analysis Methodology

The Latent Class Analysis (LCA) segments the reference population by assigning to the units of analysis different probabilities of membership to an unobserved or latent categorical variable. The LCA exploits interrelations and relationship between the labor market attributes selected in comparison to traditional regression analysis, in which the constant relationship between the predictor and the other selected attributes or covariates is assumed (Vandeninden & Ovadiya, 2017). The latent or ununobservedariable is often viewed as the missing and antecedent characteristic causing or inducing the spurious relationships among the observable attributes (Hagenaars & McCutcheon, 2002). In other applications it is instead viewed as an "intervening" variable whithatmpletely explains the associations amon among thee attributes. The latent variable is in this study defined as the "intervening" grouping variable which is able to explain canonships among the chosen labor-market attributes. LCA provides a segmentation of the reference population by maximizing the between-cluster differences and minimize the within-cluster differences (Schreiber, 2016). The technique does not automatically provide the adequate number of canses to use but requires a study of the optimal number of clusters that best represent the reference population and its respective observed attributes.

The selection and parametrization of the model begin with the implementation of a baseline model. The initial baseline model is tested through the use of labor-market attributes as predictors of cclass membershipto a multinomial latent variable. This is done by incrementing the number of classes from 2 classes to 12 classes. The goodness-of-fit statistics are then assessed across the tested models itoidentify the correct number of classes to use (Table A1, Table A2). These statistics include the G2, the log-likelihood statistics, the Akake Information Criterion (AIC), the Bayes Information Criterion (BIC) and the degrees of freedom (Nylund, Asparouhov, & Muthen, 2007). The log-likelihood reflects the logarithm of the likelihood ratio which compares the prediction of two models which differ in the number of restrictions made and it is assessed through its p-value and the chi-squared statistic, which is by convention denoted by the G^2 (G-squared). The BIC is the Bayes Information Criterion and the AIC is the Akake Information Criterion, which are statistics or "parsimony indeces" testing the number of factors included in the model.

Table A1. **Baseline comparison goodness-of-fit statistics across models, URBAN sample**

Classes	N	LL	LL Ratio	G-sq	DF	AIC	BIC
2	6313	-14,475.83	0.00	1,780.90	11.00	28,973.66	29,047.91
3	6313	-13,945.72	0.00	720.68	23.00	27,937.45	28,092.70
4	6313	-13,847.30	0.00	523.83	31.00	27,756.59	27,965.85
5	6313	-13,614.30	1.00	57.83	31.00	27,290.59	27,499.85
6	6313	-13,586.88	1.00	2.99	43.00	27,259.75	27,550.02
7	6313	-13,587.34	1.00	3.91	49.00	27,272.67	27,603.44
8	6313	-13,588.35	1.00	5.94	45.00	27,266.70	27,570.47
9	6313	-13,586.47	1.00	2.18	64.00	27,300.94	27,732.97
10	6313	-13,586.55	1.00	2.34	69.00	27,311.10	27,776.88
11	6313	-13,585.52	1.00	0.27	73.00	27,317.03	27,809.81
12	6313	-13,585.74	1.00	0.72	79.00	27,329.48	27,862.76

Source: Authors' calculations using ECAM4 (2014).

Table A2. **Baseline comparison goodness-of-fit statistics across models, RURAL sample**

Classes	N	LL	LL Ratio	G-sq	DF	AIC	BIC
2	5259	-10,802.93	0.00	1,204.08	13.00	21,631.87	21,717.25
3	5259	-10,719.81	0.00	1,037.84	20.00	21,479.63	21,610.98
4	5259	-10,702.58	0.00	1,003.38	31.00	21,467.17	21,670.77
5	5259	-10,701.43	0.00	1,001.07	31.00	21,464.86	21,668.46
6	5259	-10,285.98	0.00	170.16	32.00	20,635.95	20,846.12
7	5259	-10,203.41	1.00	5.03	53.00	20,512.82	20,860.91
8	5259	-10,589.69	0.00	777.59	58.00	21,295.38	21,676.31
9	5259	-10,592.39	0.00	783.00	63.00	21,310.78	21,724.55
10	5259	-10,201.35	1.00	0.91	49.00	20,500.70	20,822.52
11	5259	-10,280.76	0.00	159.74	56.00	20,673.53	21,041.32
12	5259	-10,201.20	1.00	0.62	73.00	20,548.41	21,027.85

Source: Authors' calculations using ECAM4 (2014).

The estimates are then assessed for identifying the restrictions to be made. More specifically, the weak-attachment attributes are not allowed in detachment classes. Once the identifying restrictions are implemented, the goodness-of-fit statistics are once more compared (Table A3, Table A4) to validate the efficiency of the method. These restrictions are implemented to increase parsimony and stability to the specification (Vermunt & Magidson, 2005) and are in every case validated by their ability to better represent the reference population and the labor-market attributes.

Once the efficiency of the restrictions is validated, the active covariates are entered into the specification and the efficiency of the specification is once more assessed (Table A3, Table A4). The introduction of covariates which have a significant effect on class-membership probabilities can further reduce miss-classification errors and improve the predictive power of the model (Wurpts & Geiser, 2014). A series of standard variables used for the analysis of the labor-market are here used and are the sex, age-group and education of youth. The introduction of the active covariates to the constrained solution has reduced the goodness-of-fit statistics across the samples studied, hence indicating a more fitting and efficient solution. A classification statistic is also implemented to provide an additional validation of the predictive and classifying effectiveness of the model. The modal allocation assigns each unit to its respective class with the highest posterior probability. The misclassification error can be measured by cross-classifying the modal assignment with the probability-based assignment (Vermunt & Magidson, 2005). The misclassification error stands as a measure of predictive effectiveness for the specification used. A statistic higher than 30% highlights that the specification is significantly not able to discriminate between classes (Fernandez et. al, 2016).

Table A3. **Goodness-of-fit statistics across models, URBAN sample**

Model	N	LL	DF	AIC	BIC
Unconstrained	6313	-13586.88	43	27259.75	27550.02
Constrained	6313	-13586.83	16	27205.66	27313.67
Complete	6269	-12446.63	52	24997.26	25347.92

Source: Authors' calculations using ECAM4 (2014).

Table A4. **Goodness-of-fit statistics, RURAL sample**

Model	N	LL	DF	AIC	BIC
Unconstrained	5259	-10203.41	53	20512.82	20860.91
Constrained	5259	-10205.31	21	20452.62	20590.54
Complete	5237	-9257.61	62	18639.22	19046.15

Source: Authors' calculations using ECAM4 (2014).

Further, we estimate the bivariate residual (or BVR statistic) which is a measure for assessing whether the observed association between two variables is well reproduced by the model. The bivariate residuals help determine whether the local independence assumption does not hold and if the model is fitting appropriately at a *local* level. If the BVR statistic for any pair of variablesis is larger than 3.84 (the critical or significance value with one degrees of freedom and the 95% confidence level) a direct effect should be included in order to improve fitting (Vermunt & Magidson, 2005). Most of the bivariate residuals computed for the urban model (Table A5) and the rural model (Table A6) are largely below 1 and therefore not concerning. Table 6 further shows that the model adopted for the rural sample may be falling short in reproducing the associations between *time-related underemployment* and *temporary employment*, *unpaid employment*, and *informality*. Besides, no direct effects are included considering that the BVR statistic for each of these associations remain below the critical value of 3.84.

Table A5. **Bivariate Residuals for Selected Urban Model**

Indicators	INI	VOI	UNE	TRU	TEM	UNP	INF
INI							
VOI	0.0005						
UNE	0.0003	0.0004					
TRU	0.0004	0.0005	0.0003				
TEM	0.0003	0.0004	0.0002	0.0820			
UNP	0.0013	0.0014	0.0012	0.0003	0.0007		
INF	0.0005	0.0005	0.0004	0.0012	0.0020	0.0001	

Source: Authors' calculations using ECAM4 (2014).

Table A6. **Bivariate Residuals for Selected Rural Model**

Indicators	INI	VOI	UNE	TRU	TEM	UNP	INF
INI							
VOI	0.0782						
UNE	0.0014	0.0773					
TRU	0.0126	0.0834	0.0140				
TEM	0.0031	0.0771	0.0044	2.1865			
UNP	0.0473	0.0803	0.0399	1.4421	0.3232		
INF	0.0034	0.0833	0.0042	2.4577	0.0576	0.2671	

Source: Authors' calculations using ECAM4 (2014).

Once the complete model is finalized and estimated, the resulting probabilities of class-membership are used for predicting the classes of the sample. The designation is in turn used for the characterization, which is undertaken by computing two-way statistics summarizing the relationship between the group-membership of the sample and the respective socio-economic

characteristics. The latter are arbitrarily chosen and based on the knowledge of covariates deemed as suitable for understanding intra-cluster dynamics and beneficial for policy-making purposes as in the case of targeting decisions, for example. The individual features adopted for the characterization are broadly represented by groups of indicators which can respectively describe the demographic, human capital, geographic, employment and income profile of the classes.

Annex 2. Detailed Group Characterization Results

Urban Characterization

Table A12. Characterisation of classes by demographic variables

	Detachment Classes			Weak-attachment Classes		
Variables	1	2	3	4	5	6
Sex						
Female	0.69	0.86	0.64	0.34	0.64	0.43
Male	0.31	0.14	0.36	0.66	0.36	0.57
Household size						
1-2	0.14	0.10	0.19	0.30	0.19	0.31
3-6	0.48	0.53	0.53	0.48	0.51	0.51
7-10	0.25	0.26	0.22	0.17	0.23	0.16
>10	0.13	0.11	0.06	0.05	0.08	0.02
Age Group						
15/19	0.14	0.15	0.07	0.00	0.19	0.00
20/24	0.27	0.32	0.24	0.18	0.33	0.06
25/29	0.40	0.32	0.43	0.37	0.30	0.34
30/35	0.18	0.22	0.27	0.45	0.18	0.60
Marital status						
Married	0.39	0.63	0.33	0.52	0.38	0.49
Single	0.60	0.35	0.66	0.46	0.61	0.51
Widowed/Divorced	0.01	0.02	0.01	0.03	0.02	0.01
Residence 12 months ago						
Different Location	0.15	0.15	0.12	0.16	0.16	0.18
Same Location	0.85	0.85	0.88	0.84	0.84	0.82
Religion						
Animism	0.01	0.00	0.01	0.00	0.01	0.00
Catholic	0.52	0.32	0.54	0.47	0.49	0.55
Muslim	0.15	0.41	0.09	0.21	0.16	0.06
None	0.01	0.02	0.01	0.03	0.03	0.02
Other Christian	0.07	0.05	0.06	0.06	0.08	0.08
Other Religion	0.04	0.02	0.04	0.03	0.04	0.04
Protestant	0.21	0.17	0.24	0.19	0.20	0.25

Source: Authors' calculations using ECAM4 (2014).

Table A13. Characterisation of classes by demographic human capital variables

	Detachment Classes			Weak-attachment Classes		
Variables	1	2	3	4	5	6
Education						
Higher	0.20	0.05	0.33	0.00	0.16	0.55
No Education	0.07	0.24	0.03	0.08	0.04	0.00
Primary	0.17	0.31	0.13	0.37	0.30	0.00
Secondary	0.55	0.40	0.51	0.55	0.50	0.45
Technical or vocational training						
No	0.50	0.69	0.40	0.40	0.39	0.21
Yes	0.50	0.31	0.60	0.60	0.61	0.79
Working experience						
0	0.49	0.52	0.27	0.01	0.08	0.03
1-2	0.04	0.04	0.04	0.04	0.11	0.04
3-5	0.09	0.08	0.15	0.10	0.19	0.10
6-9	0.09	0.09	0.14	0.16	0.18	0.17
10-15	0.17	0.13	0.24	0.33	0.25	0.28
16-20	0.09	0.09	0.12	0.22	0.12	0.24
>20	0.02	0.05	0.05	0.13	0.06	0.14

Source: Authors' calculations using ECAM4 (2014).

Table A14. Characterisation of classes by geographic variable

	Detachment Classes			Weak-attachment Classes		
Variables	1	2	3	4	5	6
Region						
Adamaoua	0.04	0.06	0.01	0.03	0.03	0.02
Center	0.01	0.01	0.01	0.01	0.01	0.01
Douala	0.31	0.24	0.36	0.34	0.31	0.39
East	0.01	0.04	0.01	0.02	0.02	0.01
Far-North	0.05	0.17	0.02	0.06	0.04	0.02
Littoral	0.01	0.02	0.01	0.02	0.02	0.02
North	0.04	0.11	0.03	0.04	0.04	0.02
North-West	0.04	0.03	0.03	0.05	0.06	0.04
South	0.01	0.02	0.01	0.02	0.02	0.02
South-West	0.05	0.04	0.06	0.07	0.08	0.06
West	0.05	0.08	0.04	0.06	0.06	0.05
Yaounde	0.37	0.20	0.43	0.29	0.32	0.36

Source: Authors' calculations using ECAM4 (2014).

Table A15. Characterisation of classes by employment variables

	Detachment Classes			Weak-attachment Classes		
Variables	1	2	3	4	5	6
Socio-Professional Category						
Employer				0.06	0.03	0.02
Executive / Managers				0.01	0.01	0.20
Family Aid				0.05	0.33	0.05
Labourer				0.12	0.10	0.11
Own account worker				0.56	0.44	0.07
Qualified employee				0.20	0.10	0.54
Industry						
Commerce				0.31	0.27	0.15
Industry				0.28	0.25	0.16
Primary				0.05	0.07	0.02
Services				0.36	0.41	0.67
Institutional sector						
Administration				0.01	0.02	0.18
Association				0.01	0.00	0.01
Household				0.03	0.04	0.04
Private (formal)				0.07	0.04	0.32
Private Agr. (informal)				0.04	0.06	0.01
Private Not Agr. (informal)				0.83	0.82	0.37
Pub. Entity/funded				0.02	0.01	0.06
Worked since age <15						
No	0.77	0.78	0.73	0.58	0.56	0.63
Yes	0.23	0.22	0.27	0.42	0.44	0.37

Source: Authors' calculations using ECAM4 (2014).

Table A16. Characterisation of classes by wealth and income variables

	Detachment Classes			Weak-attachment Classes		
Variables	1	2	3	4	5	6
Poverty						
Yes	0.08	0.10	0.05	0.07	0.09	0.02
No	0.92	0.90	0.95	0.93	0.91	0.98
Savings quintiles						
0	0.67	0.74	0.65	0.63	0.62	0.49
1	0.07	0.05	0.08	0.09	0.09	0.09
2	0.07	0.05	0.05	0.08	0.08	0.09
3	0.04	0.05	0.04	0.06	0.06	0.09
4	0.06	0.06	0.06	0.08	0.06	0.13
5	0.11	0.05	0.12	0.06	0.08	0.11
At least there a household member rear poultry/cattle						
No	0.90	0.88	0.88	0.90	0.88	0.92
Yes	0.10	0.12	0.12	0.10	0.12	0.08
Possession of financial assets (equities, property or bonds)						
No	0.99	1.00	0.98	0.99	0.99	0.98
Yes	0.01	0.00	0.02	0.01	0.01	0.02
A household member owns exploited land						
No	0.79	0.81	0.75	0.79	0.76	0.80
Yes	0.21	0.19	0.25	0.21	0.24	0.20

Source: Authors' calculations using ECAM4 (2014).

Table A17. Characterisation of classes by demographic variables

	Detachment Classes			Weak-attachment Classes			
Variables	1	2	3	4	5	6	7
Sex							
Female	0.64	0.87	0.55	0.47	0.73	0.60	0.32
Male	0.36	0.13	0.45	0.53	0.27	0.40	0.68
Household size							
1-2	0.11	0.09	0.10	0.13	0.07	0.10	0.32
3-6	0.43	0.46	0.50	0.56	0.48	0.46	0.47
7-10	0.23	0.27	0.29	0.22	0.29	0.29	0.17
>10	0.23	0.18	0.12	0.09	0.16	0.14	0.04
Age Group							
15/19	0.27	0.24	0.13	0.00	0.29	0.52	0.00
20/24	0.28	0.33	0.42	0.20	0.29	0.29	0.08
25/29	0.33	0.26	0.36	0.33	0.21	0.19	0.34
30/35	0.11	0.17	0.09	0.47	0.21	0.01	0.58
Marital status							
Married	0.35	0.65	0.46	0.72	0.60	0.36	0.63
Single	0.62	0.33	0.54	0.24	0.37	0.61	0.35
Widowed/Divorced	0.03	0.02	0.00	0.05	0.03	0.03	0.02
Residence 12 months ago							
Different Location	0.08	0.09	0.09	0.07	0.05	0.10	0.19
Same Location	0.92	0.91	0.91	0.93	0.95	0.90	0.81
Religion							
Animism	0.02	0.00	0.00	0.03	0.09	0.05	0.01
Catholic	0.32	0.22	0.34	0.26	0.19	0.29	0.35
Muslim	0.31	0.51	0.12	0.26	0.34	0.25	0.14
None	0.02	0.01	0.01	0.04	0.06	0.01	0.02
Other Christian	0.06	0.07	0.11	0.08	0.05	0.06	0.08
Other Religion	0.04	0.03	0.05	0.03	0.02	0.02	0.03
Protestant	0.24	0.16	0.36	0.30	0.26	0.31	0.37

Source: Authors' calculations using ECAM4 (2014).

Table A18. Characterisation of classes by demographic human capital variables

	Detachment Classes			Weak-attachment Classes			
Variables	1	2	3	4	5	6	7
Education							
Higher	0.10	0.01	0.04	0.00	0.00	0.08	0.33
No Education	0.27	0.43	0.07	0.26	0.50	0.02	0.03
Primary	0.34	0.35	0.39	0.48	0.39	0.41	0.19
Secondary	0.29	0.21	0.50	0.26	0.11	0.49	0.45
Technical or vocational training							
No	0.77	0.86	0.51	0.74	0.86	0.66	0.24
Yes	0.23	0.14	0.49	0.26	0.14	0.34	0.76
Working experience							
0	0.69	0.71	0.36	0.01	0.04	0.11	0.02
1-2	0.02	0.02	0.01	0.02	0.04	0.07	0.01
3-5	0.05	0.04	0.14	0.06	0.17	0.27	0.16
6-9	0.07	0.07	0.11	0.11	0.22	0.23	0.15
10-15	0.10	0.12	0.31	0.33	0.31	0.23	0.29
16-20	0.05	0.03	0.05	0.29	0.17	0.07	0.22
>20	0.02	0.02	0.02	0.18	0.05	0.01	0.14

Source: Authors' calculations using ECAM4 (2014).

Table A19. Characterisation of classes by geographic variable

	Detachment Classes			Weak-attachment Classes			
Variables	1	2	3	4	5	6	71
Region							
Adamaoua	0.12	0.20	0.15	0.07	0.04	0.05	0.10
Center	0.14	0.13	0.22	0.08	0.09	0.10	0.11
East	0.04	0.12	0.07	0.06	0.04	0.07	0.09
Far-North	0.24	0.17	0.07	0.21	0.44	0.22	0.07
Littoral	0.02	0.03	0.05	0.03	0.01	0.02	0.05
North	0.09	0.12	0.03	0.20	0.22	0.08	0.07
North-West	0.17	0.08	0.21	0.12	0.05	0.19	0.18
South	0.04	0.06	0.05	0.05	0.01	0.04	0.09
South-West	0.10	0.06	0.06	0.11	0.03	0.14	0.14
West	0.04	0.03	0.08	0.08	0.07	0.09	0.10

Source: Authors' calculations using ECAM4 (2014).

Table A20. Characterisation of classes by employment variables

	Detachment Classes			Weak-attachment Classes			
Variables	1	2	3	4	5	6	7
Socio-Professional Category							
Employer				0.02	0.00	0.02	0.00
Executive / Managers				0.00	0.00	0.00	0.24
Family Aid				0.03	0.66	0.55	0.02
Labourer				0.04	0.01	0.06	0.18
Own account worker				0.89	0.32	0.35	0.04
Qualified employee				0.03	0.01	0.02	0.52
Industry							
Commerce				0.11	0.04	0.11	0.06
Industry				0.13	0.06	0.18	0.12
Primary				0.65	0.86	0.54	0.13
Services				0.11	0.04	0.17	0.70
Institutional sector							
Administration				0.00	0.00	0.02	0.47
Association				0.00	0.00	0.00	0.01
Household				0.02	0.01	0.05	0.01
Private (formal)				0.00	0.00	0.01	0.16
Private Agr. (informal)				0.62	0.85	0.54	0.04
Private Not Agr. (informal)				0.35	0.14	0.37	0.20
Pub. entity/funded				0.01	0.00	0.00	0.12
Worked since age <15							
No	0.81	0.86	0.77	0.44	0.32	0.39	0.59
Yes	0.19	0.14	0.23	0.56	0.68	0.61	0.41

Source: Authors' calculations using ECAM4 (2014).

Table A21. Characterisation of classes by wealth and income variables

	Detachment Classes			Weak-attachment Classes			
Variables	1	2	3	4	5	6	7
Poverty							
Yes	0.46	0.49	0.30	0.49	0.68	0.45	0.19
No	0.54	0.51	0.70	0.51	0.32	0.55	0.81
Savings quintiles							
0	0.77	0.85	0.75	0.82	0.87	0.79	0.61
1	0.05	0.02	0.04	0.04	0.04	0.06	0.03
2	0.03	0.03	0.10	0.03	0.03	0.06	0.07
3	0.04	0.03	0.05	0.04	0.03	0.03	0.07
4	0.06	0.03	0.02	0.04	0.02	0.04	0.14
5	0.06	0.04	0.05	0.02	0.02	0.03	0.08
At least there a household member rear poultry/cattle							
No	0.64	0.63	0.73	0.56	0.43	0.56	0.70
Yes	0.36	0.37	0.27	0.44	0.57	0.44	0.30
Possession of financial assets (equities, property or bonds)							
No	0.98	0.99	0.99	0.99	1.00	0.99	0.98
Yes	0.02	0.01	0.01	0.01	0.00	0.01	0.02
A household member owns exploited land							
No	0.41	0.41	0.41	0.26	0.15	0.23	0.53
Yes	0.59	0.59	0.59	0.74	0.85	0.77	0.47

Source: Authors' calculations using ECAM4 (2014).

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