Youth Jobs, Skill and Educational Mismatches in Africa

Morsy, Hanan and Mukasa, Adamon

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Hanan Morsy[1] and Adamon N. Mukasa[2]

Abstract

This paper contributes to the empirical literature on the incidence of skill and educational mismatches of African youth and explores the linkages between job mismatch and wages, job satisfaction, and on-the-job search. It uses school-to-work transition survey datasets from 10 African countries and controls for unobserved heterogeneity, sample selection bias and endogeneity problems during the estimation of job mismatch. Results show that skill and educational mismatches are prevalent in Africa: 17.5% of employed youth are overskilled, 28.9% underskilled, 8.3% overeducated and 56.9% undereducated. Our estimation results reveal that overskilling and overeducation are associated with a wage penalty and undereducation leads to a wage premium. In addition, both overskilling and overeducation reduce job satisfaction and increase youth's likelihood of on-job search. Our pseudo-panel approach also suggests that skill and educational mismatches of youth are persistent over time and skill-mismatched youth are more likely to transition to better-matched jobs than youth with inadequate education. Finally, our results show that unemployment has a scarring effect for underskilled youth and both a scarring effect and a stepping-stone effect for overskilled and overeducated youth. The findings have important policy implications on how to address the persistent skill and educational mismatches among employed African youth..

JEL classification: I21, J13, J24, J28, J31

Keywords: Youth, skill mismatch, educational mismatch, wage penalty, Africa

[1] African Development Bank, Abidjan, Côte d'Ivoire.
[2] African Development Bank, Abidjan, Côte d'Ivoire (corresponding author).

1. Introduction

The past decade has seen a significant increase of the African youth population (15–35 years old). Recent projections indicate that Africa will remain the world's youngest region, with the median age of its population under 25 years old and the number of youth expected to increase from 454 million in 2020 to 845 million in 2050 and 1.2 billion in 2100 (UN, 2019). At the same time, the average educational attainment of African youth population has increased considerably. The average net enrolment in primary, secondary and tertiary education has reached 78%, 35% and 10%, respectively, in 2017 compared with 60%, 21% and 5% in 2000 (UNESCO, 2019). Based on current trends, secondary education completion rates by youth aged 20–24 will increase from 42% today to 59% in 2030, representing about 137 million youth with secondary education and 12 million with tertiary education (The Montpellier Panel, 2014).

While African countries can tap into this demographic dividend and the increasing share of better educated youth can help the continent bridge its productivity gap, researchers and development practitioners have questioned not only the quality of education acquired by graduated African youth but also the absorptive capacity of Africa's labor markets (Monga et al., 2019). In fact, although many African countries have allocated considerable resources to improve education quality (on average, they have devoted 0.78% of GDP to tertiary education, compared with 0.66% in other developing countries (Devarajan et al., 2011), these countries continue to exhibit unsatisfactory educational outcomes and their graduates often lack the appropriate skills and qualifications required by employers in many industries and sectors. This has led to skill and educational mismatches of African youth, whereby graduate youths' skills and qualifications do not correspond to requirements of available jobs (Duncan and Hoffman, 1981; Sicherman, 1991; Hartog, 2000; Borghans and de Grip, 2000; Allen and van der Velden, 2001; Green and McIntosh, 2007; Bennett and McGuinness, 2009). Together with labor market rigidities and labor mobility barriers, skill and educational mismatches represent the one of the most important costly factors for African labor markets.

Skill mismatches have potentially adverse effects at both the individual, firm and macro levels. At the individual level, high skill mismatches are likely to affect wage salaries, reduce job satisfaction and increase the likelihood of frequent job changes (Mincer, 1974; Verdugo and Verdugo, 1989; Daly et al., 2000; Dolton and Vignoles, 2000; Allen and van der Velden, 2001; Chevalier and Lindley, 2009). At the firm level, the inability to find skilled workers to perform required jobs has important repercussions on firm dynamism, productivity and profit, global competitiveness, growth and—sometimes—firm survival (AfDB, 2019). In many instances, owing to skill shortages and skill gaps, firms in Africa are forced to fill job vacancies that require skilled employees with lower-skilled workers, thereby impeding their productivity and profitability. An inadequately educated workforce has been cited among the most important obstacles to doing business in Africa, regardless of firm size and sector (AfDB, 2019). At the macro level, structural skill deficits can lead to a country's loss of competitiveness and exacerbate unemployment problems (Boll et al., 2014). It is estimated indeed that only 3 million formal jobs are created annually in Africa (Fox et al., 2013) despite the 10–12 million African youth that enter the workforce each year (AfDB et al., 2012). Closely related to skill mismatch is the phenomenon of educational mismatch (Duncan and Hoffman, 1981; Groot and van den Brink, 2000; Hartog, 2000; McGuinness, 2006), which occurs when employees work in jobs that nominally require either less (in which case they are called "undereducated") or more ("overeducated") education than they possess (see Leuven and Oosterbeek, 2011, for a survey on the topic).

Although the debate on the effects of job mismatch is not recent, the empirical evidence for developing countries, and in particular for Africa, is sparse, if not non-existent. In developed countries, empirical studies suggest that the average incidence of skill and educational mismatches is about 29% and 22%, respectively (Groot and van den Brink, 2000; McGuinness, 2006; see Cedefop, 2010 for a survey). Most existing studies of youth jobs in Africa only cite skill and/or educational mismatches as a cause of higher youth unemployment. While these studies recognize that job mismatches are likely to be pervasive and costly for African labor markets, either they do not provide supportive empirical facts or they only report case study results and anecdotal evidence (World Bank, 2015; Honorati and de Silva, 2016; McKenzie, 2017).

The objective of this paper is to fill this empirical gap by revisiting the empirical literature of skill and education mismatches in African countries. A work similar to ours is that of Herrera and Merceron (2013) who studied underemployment and job mismatch in sub-Saharan Africa. Using data from the 1-2-3 surveys conducted in seven West African countries (Benin, Burkina Faso, Côte d'Ivoire, Mali, Niger, Senegal, and Togo), Cameroon, Madagascar and the Democratic Republic of Congo (DRC) between 2001 and 2005, they found that 14.8–25.0% of employed workers aged 15 years and older are undereducated while 20.7–21.3% are overeducated. However, their study only covers urban areas and does not focus on youth.

Our paper contributes to the empirical literature on job mismatch in Africa in three ways. First, it examines the incidence of skill and educational mismatches of employed youth (aged 15¬–29) from a sample of 10 African countries between 2012 and 2015. Furthermore, the paper discusses the patterns of skill and educational mismatches by country, gender, field of study, firm size, sector of activity of employed youth and other relevant characteristics to identify common features and group specificities. Second, the paper estimates the key drivers of both skill and educational mismatches, accounting for country heterogeneity, endogeneity issues and potential measurement errors. Finally, the study examines the effects of skill and educational mismatches on wages of employed, job satisfaction, and job change. It finally discusses the job mismatch persistence over time and approximates its aggregate effects on African economies.

Our study relates to different strands of literature on job mismatch. First, it relates to the Human Capital Theory, which excludes the existence of an over-skilled or overeducated workforce in the equilibrium and considers job mismatch as a purely temporary phenomenon of maladjustment between a firm's job requirements and the existing human capital of its labor force (Becker, 1993). Under this theory, either the labor demand (firms) will adjust to adapt to the available human capital stocks or the labor supply (workers) will not invest in unnecessarily high levels of education or undesirable skills. The second theory is the Matching Theory (Pissarides, 2000), which also treats mismatch in the labor markets as a temporary phenomenon that eventually disappears in the long run because mismatched workers will end up changing jobs to improve their match. However, the persistence of skill and educational mismatches in most societies has proven difficult for both the Human Capital and the Mismatch theories (Dolton and Vignoles, 2000; Frenette, 2004; McGuinness and Wooden, 2007). Alternative models proposed include: i) the Job Mobility Theory (Sicherman and Galor, 1990; Sicherman, 1991), which assumes that workers get into overeducated positions because they lack clear signals about their productivity and, with more work experience, they will move to better matched jobs and step out of the overeducation state; ii) the Job Competition Model (Thurow, 1975), which assumes that, in a highly competitive labor market, workers always have an incentive to invest in more education and therefore, overeducation is workers' strategic response to compete for scarce better jobs; and, finally, iii) the Assignment Theory (Sattinger, 1993; Allen and van der Velden, 2001), which hypothesizes that the returns to additional investments in human capital depend in part on the match between the worker and the job.

The rest of the paper is organized as follows. Section 2 describes the datasets and discusses the characteristics of mismatched youth in the labor markets. Section 3 explains the econometric approach adopted in the paper to estimate the drivers of skill and educational mismatches, their effects on wages, job satisfaction and on-job search. The estimation results are presented and discussed in Section 4. Section 5 discusses different model extensions. Section 6 concludes and discusses key policy implications of the findings.

2. Data and descriptive analysis

The data used for the analysis are cross-sectional datasets from the School-To-Work Transition Surveys (SWTS) carried out by the International Labor Organization (ILO) in 10 African countries between 2012 and 2015 : Benin, Egypt, Liberia, Malawi, Togo, and Zambia (2012 and 2014), Madagascar and Uganda (2013 and 2015), Tanzania (2013) and Congo (2015). The surveys are nationally representative of the youth population (15–29 years old) and cover employed, unemployed, full-time student and inactive youth. The survey design is similar across countries and time, which allows both cross-country and temporal comparisons. The data contain a rich set of variables related to family background, educational attainment, employment history and current employment status of youth as well as future employment prospects of unemployed youth and students. The full sample consists of 64,310 African youth, of whom 32,437 are employed (Table 2.1).

Table 2.1: Sample distribution of youth by country, year, and employment status

		Sample		
Country	Year	Total	Employed	Unemployed
Benin	2012	6,917	1,830	5,087
	2014	4,306	946	3,360
Congo	2015	3,276	1,139	2,137
Egypt	2012	5,198	2,625	2,573
	2014	5,758	1,785	3,973
Liberia	2012	1,876	908	968
	2014	2,416	1,379	1,037
Madagascar	2013	3,300	2,614	686
	2015	5,044	3,867	1,177
Malawi	2012	3,102	1,980	1,122
	2014	3,097	2,103	994
Tanzania	2013	1,988	769	1,219
Togo	2012	2,033	1,267	766
	2014	2,708	1,576	1,132
Uganda	2013	3,811	2,453	1,358
	2015	3,049	1,961	1,088
Zambia	2012	3,206	1,428	1,778
	2014	3,225	1,807	1,418
Total		64,310	32,437	31,873

Source: Authors' computations based on ILO SWTS data, various countries and years.

We used information contained in the surveys to construct our mismatch variables. Skill mismatch corresponds to a situation in which an employed youth, during the period under consideration, occupied a job whose skill requirements did not correspond to the youth's actual or self-perceived skills. However, measuring skill mismatch is particularly challenging because not only there is no internationally agreed classification of skills or standard measure of skills (ILO, 2018)[3] but also different job occupations may require different types of skills, while the skills needed for the same occupation might change over time as some skills become obsolete (Allen and de Grip, 2011). However, there are three main measures of skill mismatch in the literature, each one with its own advantages and disadvantages: direct assessment, employers' assessment and workers' assessment. Direct assessment approaches are based on questions concerning selected types of skills (numeracy, literacy, writing, reading skills, etc.). Workers are often given assessment tests designed to directly measure a specific skill or their capacity to solve complex problems. Standardized scales of skills can then be derived and individuals are then classified as skill mismatched depending on whether the standardized value of their skills is above or below some predefined cut-off point[4]. However, this approach is relatively time-consuming and data-demanding as it requires very detailed job and occupation analyses and precise skills testing (Allen et al., 2013). Employers' assessment techniques consist of collecting employers' own perceptions of the skills possessed by their workforce and the skills needed by their respective job. Though interesting, these techniques require expensive large-scale surveys and are based on the fundamental assumption that employers are capable of assessing the actual skill level of each of their workers. Finally, workers' self-assessment measures are based on employees' self-perceived match between their skills and the skills needed to perform their job competently. The obvious drawback of this method is that workers may tend to overestimate their own skills or those required for their jobs. The main advantage of this approach is that it takes into account the heterogeneity of jobs since workers can be considered the most knowledgeable person about their own jobs and the spectrum of skills needed to perform their work efficiently. The choice of either method is mainly conditional on data availability, as none of the above methods has been shown to outperform the others (ILO, 2018).

Our datasets only allow us to apply the workers' self-assessment approach. Despite its subjectivity, the approach has been found to produce reliable results on measuring skill mismatch (Allen and van der Velden, 2001; Green, 2013). Hence, we define skill mismatch using self-assessment of employed youth about their skill mismatch. Each employed youth was asked the following question: *"Do you feel that your education/training qualifications/skills*

[3] For instance, O*Net lists 35 skills classified into 6 groups, while the ESCO classification of skills considers 13,485 different skills/competences (ILO, 2018).
[4] For instance, Allen et al. (2013) used 1.5 points above or below zero as their cutting point of skill mismatch.

are relevant in performing your present job?" with 3 potential answers of interest: a) "Yes, I feel that they adapt to my job" (we classify the youth as *well-matched*); b) "No, I feel overqualified" (s/he is classified as *overskilled*); c) "No, I feel underqualified and experience gaps in my knowledge and skills and need more training" (s/he classified as *underskilled*).

Closely related to the notion of skill mismatch is the concept of educational mismatch which refers to the situation where a worker's level of education does not correspond to the required level of education to perform his or her job or when the individual's field of study is different from the required field of study (Leuven and Oosterbeek, 2011). Although sometimes used interchangeably, skill and educational mismatches do not refer to the same phenomenon: two workers with the same level of education may have completely different levels of skills and abilities or the other way around. In addition, while people's level of education rarely changes once they have completed their formal education and have started working, their skills can vary substantially during the course of their work lifetime through on-job training, experience, self-learning, etc. Hence the need to analyze both types of job mismatch separately. To compute our educational mismatch variable, we use the job analysis framework introduced by Eckaus (1994). It is a normative approach based on job experts assessment of the educational requirements of each occupation group (Capsada-Munsech, 2019). Educational mismatch is defined by comparing the actual and the required levels of education using the International Standard Classification of Occupations (ISCO) (ILO, 2012). Each occupation group is assigned a required level of education in accordance with the International Standard Classification of Education (ISCED) (UNESCO, 2012)[5]. A worker is then classified as *well-matched* if his or her highest level of acquired education is equal to the required level of education of his or her ISCO group[6]. S/he is classified as over (under) educated if his or her actual education level is greater (lower) than the required education level.

Figure 2.1 provides the incidence of skill and educational mismatches in the surveyed countries. It shows that both skill and educational mismatches are pervasive among employed African youth. On average, 53.6% of employed youth considered their skills appropriate given the requirements of their current job. This means that around 46.4% of employed youth in the

[5] To ensure comparability of education systems across countries, we harmonized the education level as follows: no education, primary education, secondary education and tertiary education using ISCED classification.

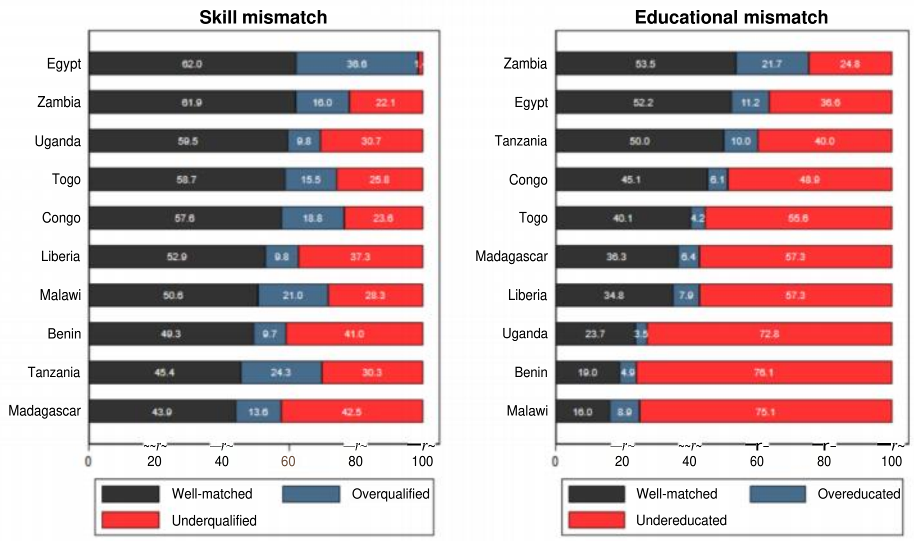
[6] For instance, if an employed youth occupies a managerial position in his company while having only a secondary level education, then s/he is classified as undereducated compared with the requirements of his/her job (having a university degree). Conversely, if a graduate youth ends up doing elementary occupations (cleaner, housekeeper, fruit picker, etc.), he is labeled overeducated because these occupations only require a primary education level.

selected countries perceived their skills ill-matched with their jobs: 17.5% feel overskilled and the remaining 28.9% experience skill deficits. There is, however, important cross-country heterogeneity. The largest shares of well-skilled youth are found in Egypt (62%), Zambia (61.9%), and Uganda (59.5%), while employed youth in Madagascar (43.9%), Tanzania (45.4%) and Benin (49.3%) display the smallest shares. In all countries but Egypt, the proportion of youth with perceived underskilling is greater than that for the overskilled, which tends to confirm the hypothesis that youth in Africa experience important skill deficits. Underskilling is more widespread in Madagascar (42.5%), Benin (41%) and Liberia (37.3%), while in Egypt it concerns only 1.4% of youth.

In terms of educational mismatch, the education level of only 34.8% of employed youth corresponds to the education normally required for their current job, implying that close to two-thirds of African youth are working with an educational attainment either lower (undereducation) or higher (overeducation) than their job requirements. Most young workers are undereducated (56.9%) and only 8.3% are overeducated, in contrast with youth from developed countries, where overeducation is more pervasive than undereducation. Similar to underskilling, undereducation is more frequent than overeducation in the selected African countries. In Malawi for instance, about three-quarters of employed youth are undereducated while in Zambia, only 24.9% are concerned.

Figure 2.1: Incidence of youth's skill and educational mismatches in selected African countries

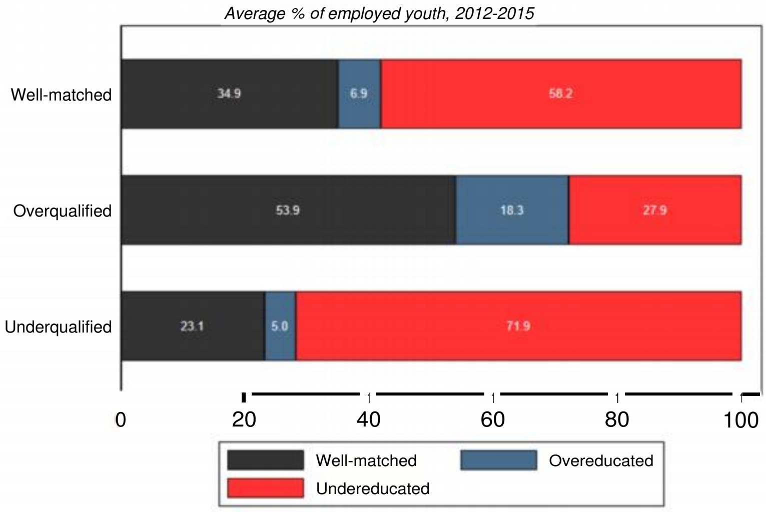
Average % of employed youth per country, 2012-2015



Source Authors' computation based on ILO's STWT data, various countries and years

The relationship between skill and educational mismatches appears imperfect in the selected countries (Figure 2.2). For instance, among well-skilled youth, only 34.9% possess the right level of education. In 71.9% of cases, underskilled youth are also undereducated while only 18.3% of overskilled youth are also overeducated. This fact suggests that the problem of job mismatch in Africa is bi-dimensional as it concerns both the *quantity* of education (educational attainment) and its *quality* (skills and qualification acquired). In addition, these preliminary results imply that possessing the required level of education is neither a necessary nor a sufficient condition for better utilization of skills (Allen and van der Velden, 2001; Allen and De Weert, 2007; Mavromaras et al., 2010). Accordingly, the question is to identify which covariates determine the occurrence of skill and educational mismatches at the same time, and which characteristics prevail in determining one or the other form.

Figure 2.2: Relationship between skill and educational mismatches



Source: Authors' computation based on ILO's STWT data, various countries and years

The differences in youth's characteristics by job mismatch status are reported in Table 2.2. Some interesting features emerge. On average, employed female youth are better matched and more likely to be overskilled than their male counterparts whereas underskilling is more pervasive among males. On the education side, female youth are also more likely to be both better matched and overeducated, in contrast with results from developed countries where the incidence of overeducation is often found to be either not gender-related (Chevalier, 2003) or in favor of males (Boll and Leppin, 2014). However, important cross-country differences exist (see Figure A.1): In Egypt, Congo, and Benin for instance, employed males are more likely to have the required skills and education than females, while in Uganda and Malawi, it is the other way around. Gender gaps among overqualified youth are more important in Egypt, Togo and Tanzania.

In addition, we also observe that the incidence of skill mismatch is more associated with poor education—overskilling (underskilling) is increasing (decreasing) with higher education—and appears to decline as the youth move to higher age cohorts, in line with human capital theories. Mismatched youth are also more likely to live in rural areas and in bigger households. Interestingly, the table suggests that parents' education and the skill content of their jobs are correlated with the incidence of skill and educational mismatches of their young children: larger shares of well-matched employed youth are found in families where parents are either better educated or work in skilled jobs or both. In terms of employment characteristics of the youth, Table 2.2 shows that the incidence of job mismatch is positively correlated with poor or precarious working conditions. Youth in vulnerable employment (self-employed, working without a contract and/or on short-term contract) or working in agriculture are more likely to experience skill deficits and lack the appropriate level of education.

Regarding the wage salary, well-matched workers earn on average more than mismatched youth whereas underskilled are better remunerated that overskilled, in support of mismatch models that predict a wage penalty for overskilled workers and a wage premium for underskilled (Bauer, 2002; Verhaest and Omey, 2006, 2012). Furthermore, better skills and education attainment are positively correlated with the firm size, implying that large firms have better chances to attract or easily identify well-matched workers in the labor markets. Indeed, the proportion of youth with well-matched skills increases from 52% in firms with less than 10 workers to 62.5% in firms with 10–49 employees and up to 74.5% in large firms with more than 500 workers. A similar pattern is observed with the educational mismatch.

Finally, skill mismatches appear to be negatively correlated with the degree of job satisfaction: the higher the incidence of skill mismatch, the lower the likelihood of being satisfied by the job (Allen and van der Velden, 2001; Johnson and Johnson, 2002; Florit and Lladosa, 2007). However, this association is not clear when it comes to educational mismatches. Indeed, while the incidence of overeducation is negatively associated with the level of job satisfaction, youth become more satisfied as the incidence of undereducation increases, suggesting that skill and educational mismatches might have heterogeneous effects on job satisfaction.

Table 2.2: Differences in employed youth characteristics by type of skill and educational mismatches

Characteristic	Skill mismatch			Educational mismatch		
	Well-matched	Overskilled	Underskilled	Well-matched	Overeducated	Undereducated
Personal characteristics						
Gender						
Male	53.04	14.06	32.89	31.64	7.01	61.34
Female	53.84	20.54	25.62	37.04	9.49	53.47
Marital status						
Married	53.09	12.37	34.54	29.02	6.11	64.87
Single	53.18	21.33	25.49	40.79	10.80	48.41
Education						
No education	53.02	6.56	40.43	-	-	100.00
Primary education	55.11	10.81	34.08	15.64	-	84.36
Secondary education	53.65	29.59	16.76	75.16	14.18	10.66
Tertiary education	58.43	35.45	6.11	47.74	52.26	-
Field of study						
General programs	57.56	20.46	21.98	22.22	2.78	75.00
Education	64.22	16.82	18.96	21.14	5.69	73.17
Arts & Literature	51.85	31.48	16.67	33.33	-	66.67
Social sciences	58.16	30.86	10.98	26.01	8.07	65.92
Sciences, Math, ICT	61.99	23.39	14.62	29.17	6.30	64.57
Engineering	62.94	23.86	13.20	46.09	18.26	35.65
Agriculture	66.67	21.74	11.59	38.64	15.91	45.45
Health	54.09	27.24	18.68	53.33	20.00	26.67
Other services	47.96	9.92	42.12	33.33	8.57	58.10
Age	22.85	22.51	22.43	23.20	23.31	22.68
Age groups						
Between 15 & 29 years	50.92	17.56	31.51	28.57	6.50	64.93
Between 20 & 24 years	52.42	19.62	27.97	38.26	9.52	52.22
Between 25 & 29 years	56.06	16.62	27.32	35.67	8.87	55.46
Age of first marriage	17.38	18.55	16.02	18.85	20.02	15.96
Number children	1.74	1.58	1.88	1.56	1.40	1.79
Relation with the head						
Head	56.25	12.91	30.84	33.27	7.54	59.19
Spouse	51.39	10.58	38.03	21.86	4.27	73.87
Son/daughter	51.81	19.04	29.14	33.97	8.80	57.23
Family characteristics						
Household size	5.60	5.68	5.83	5.58	5.54	5.69
Location						
Rural	52.19	15.64	32.17	30.87	6.90	62.23
Urban	56.00	21.05	22.95	41.78	11.18	47.04
Father's education						
No education	50.34	14.52	35.14	24.81	4.10	71.09
Primary education	53.10	17.70	29.20	32.37	6.72	60.91
Secondary education	54.86	23.34	21.80	49.11	15.31	35.58
Tertiary education	69.19	19.47	11.34	55.78	21.35	22.87
ISCO skill level of father's work([a])						
Skilled work	60.88	24.18	14.93	49.09	14.92	35.99
Semi-skilled work	52.10	16.07	31.84	31.42	6.52	62.06
Unskilled work	54.88	20.78	24.34	37.07	12.32	50.60
Mother's education						
No education	51.46	16.32	32.23	28.01	5.39	66.60
Primary education	52.84	17.30	29.86	35.24	8.23	56.52
Secondary education	59.49	23.63	16.88	54.37	18.58	27.05
Tertiary education	68.12	21.74	10.14	61.11	23.89	15.00
ISCO skill level of mother's work([a])						
Skilled worker	61.12	31.22	7.66	50.77	13.08	36.15
Semi-skilled worker	51.61	14.57	33.82	29.50	6.27	64.23
Unskilled worker	56.22	20.08	23.70	40.49	12.13	47.38
Employment characteristics						
Hourly wage ([b])	2.21	1.57	1.70	1.96	1.75	1.41
Employment status						
Wage employment	62.16	23.62	14.22	46.60	12.64	40.76

Self-employment	51.71	14.30	33.99	27.23	5.81	66.96
Employer	60.28	15.12	24.60	38.48	8.05	53.47
ISCO skill-level of youth work([a])						
Skilled work	75.52	13.80	10.68	39.88	-	60.12
Semi-skilled work	51.81	17.49	30.70	32.38	4.10	63.52
Unskilled work	50.60	18.97	30.43	43.27	36.70	20.03
Sector						
Agriculture	47.17	14.33	38.50	26.42	4.14	69.44
Industry	58.44	17.90	23.66	39.60	9.82	50.58
Services	58.77	20.65	20.57	40.73	11.88	47.39
Type of contract						
Written contract	74.90	13.99	11.11	51.13	14.81	34.07
Verbal contract	55.78	25.08	19.15	44.91	12.10	42.99
No contract	36.84	44.74	18.42	26.09	3.26	70.65
Duration of contract						
Less than 1 year	54.83	20.95	24.23	39.38	15.33	45.30
Between 1 & 3 years	65.34	19.89	14.77	50.00	16.95	33.05
More than 3 years	69.44	11.57	18.98	47.67	11.92	40.41
STWT duration([c])	18.17	13.81	17.50	13.12	14.42	20.20
Work experience ([d])	2.75	1.67	3.74	1.88	1.08	3.58
Number of jobs in the past	1.16	1.17	1.05	1.28	1.13	1.16
Firm size						
Less than 10 workers	51.86	17.31	30.83	33.43	7.71	58.87
Between 10 & 49	62.48	18.29	19.23	44.43	13.06	42.51
Between 50 & 499	70.38	17.60	12.02	54.04	15.89	30.08
More than 500	74.53	18.58	6.89	53.80	18.44	27.77
Job satisfaction						
Very satisfied	67.13	8.87	24.00	33.26	6.90	59.84
Satisfied	56.33	15.63	28.04	35.15	7.51	57.35
Unsatisfied	40.00	23.62	36.38	35.16	9.77	55.08
Very unsatisfied	38.13	29.23	32.64	36.40	13.84	49.76
Observations	14,697	4,797	7,997	8,323	2,011	13,752

Notes: ([a]) ISCO skill levels refer to ILO's international classification of the required skill content of different occupations based on the nature of work performed, the level of formal education attained and the amount of informal on-job training received. We put into the skilled work category ISCO major groups 1–3; semi-skilled work concerns ISCO major groups 4–8; and unskilled work concern ISCO major group 9 (elementary occupation) and armed force occupations (ILO, 2012). ([b]) Hourly wages are reported in U.S. dollars for comparability across countries. ([c]) STWT duration refers to school-to-work transition in the number of months between the end of formal education and the first professional employment experience. ([d]) Work experience is approximated by the difference between the year of the survey and first year of professional experience. For continuous variables (age, age of first marriage, number of children, household size, hourly wage, STWT duration, work experience, and number of jobs held in the past), we report means instead of proportions. The proportions are reported in reference to each characteristic so that the sum of shares for each characteristic equals 100% (or about 100% due to rounding). Source: Authors' computations based on ILO's STWT data, various countries and years.

3. Data and descriptive analysis

3.1 Model of drivers of skill and educational mismatches

3.1.1 Model specification

We use a probit-selection multinomial logit model to estimate the likelihood for employed youth to be mismatched or not in Africa's labor markets. This specification allows us to jointly account for all potential mismatch outcomes of youth while also addressing the problem of sample selection bias given that the outcome variables are only observed when youth are employed. As highlighted in the previous section, the datasets contain information on different categories of youth (employed, unemployed, inactive, and full-time student) with different socioeconomic characteristics. If these different subgroups of youth are systematically and intrinsically different in terms of characteristics, attributes and opportunities related to labor markets, then ignoring sample selection problem will lead to biased and inconsistent estimates of drivers of job mismatch. In our case, the two-step estimation procedure consists of estimating, in the first stage (selection equation), the probability of being employed, and, in the second stage, the likelihood of being mismatched (outcome equation) conditional on being employed (Ordine and Rose, 2009).

Following Gao et al. (2014), our probit-selection multinomial logit model is written as follows:

$y_i = \beta_j' Z_i + \varepsilon_i$, observed only if $w_i = 1$ (1)

$$\text{Prob}(y_i = j, w_i = 1 | Z_i,) = \Lambda(\beta_j' Z_i) = \frac{\exp(\beta_j' Z_i)}{\sum_{k'=1}^{J} \exp(\beta_k' Z_i)} \tag{2}$$

where $\Lambda(\cdot)$ is a multinomial log function, Z_i is a vector of exogenous variables explaining the outcome y_i for the i^{th} youth. Specifically, the vector Z_i includes[7] the following personal and family characteristics: gender, marital status, level of education[8] and field of study, location, age group, head of the household, parents' education and employment status and the following employment characteristics: youth's employment status, ISCO skill-level of youth job, sector of employment, type and length of current contract, work experience and firm size, as well as country and year dummies. β_j is a vector of coefficients to be estimated; ε_i is the error term. In the skill mismatch model, the dependent variable y_i is a categorical variable taking values $j = 1$ if the employed youth is *overskilled;* $j = 2$ if *underskilled* and 3 if *well matched* (the base category). In the educational mismatch model, y_i takes the values $j = 1$ if the employed youth is *overeducated*; $j = 2$ if *undereducated* and 3 if *well matched* (the base category).

The selection mechanism (being employed or not) is determined by equation (3):

$$w_i^* = X_i' \gamma_i + \mu_i, \quad \mu_i \sim (0; 1),\ w_i = 1\ if\ w_i^* > 0 \text{ and } w_i = 0 \text{ otherwise} \tag{3}$$

while the probability of being employed or not is given respectively by equations (4) and (5):

[7] See Table 2.

[8] In the educational mismatch model, we excluded the variable "education level" because it had already been accounted for when computing the educational mismatch variables.

$$\text{Prob}(w_i = 1|X_i) = \Phi(X_i'\gamma_i) \quad (4)$$

$$\text{Prob}(w_i = 0|X_i) = 1 - \Phi(X_i'\gamma_i) \quad (5)$$

where $\Phi(.)$ is the standard normal cumulative distribution function; w_i^* is a latent variable. If $w_i^* > 0$, then the observed dummy variable $w_i = 1$ and otherwise $w_i = 0$. Hence, $\text{Prob}(y_i = j|Z_i)$ is observed only if $w_i = 1$. X_i is a vector of exogenous variables affecting the probability of being employed or not; γ_i is a vector of coefficients to be estimated; and μ_i is the error term assumed normally distributed. In the selection equation, we assume that the likelihood of being employed depends on personal characteristics (age, gender, marital status, location, and being household head), education (level of education attained and field of study) and parents' education (father's and mother's level of education), as well as country and year dummies.

3.1.2 Unobserved heterogeneity

Equations 1-4 assume that the probability of being in a particular state j is conditional only on observed characteristics Z_i which vary between youth, and that the error terms ε_i and μ_i are uncorrelated. They implicitly assume that all youth with the same level of education and skills are perfect substitutes in the labor markets and that the assignment of youth between employed and unemployed groups is a totally random process. However, as pointed out by Chevalier (2003) and Tarvid (2013), in addition to observed factors in Z_i, some unobserved individual- or job-specific factors might also make the employed youth a better-matched or mis-matched candidate for the job. For instance, ability and personality attributes as well as the environment in which the youth was born and or brought up have been found to significantly explain mismatch probabilities (Allen and Van der Velden, 2001; Chevalier, 2003; Green and McIntosh, 2007; Chevalier and Lindley, 2009). Not accounting for unobserved heterogeneity in modelling the drivers of skill and educational mismatches might therefore introduce a bias on the estimated coefficients, particularly if the probability of being well- or mismatched is highly correlated with unobserved individual characteristics (Bauer, 2002; Korpi and Tåhlin, 2009).

To account for individual-level unobserved heterogeneity (individual effects) ω_i, we follow Train (2003) and adjust equation 2 as follows:

$$\text{Prob}(y_i = j, w_i = 1|Z_i, \omega_i) = \frac{\exp(\beta_j' Z_i + \omega_{ij})}{\sum_{k'=1}^{J} \exp(\beta_k' Z_k + \omega_{ik})} \quad (6)$$

where the choice probabilities are now also conditioned on unobserved heterogeneity ω_i.

The simulated log-likelihood function for the probit-selection multinomial logit model with unobserved heterogeneity has the following form (Terza, 2002; Train, 2003; Haan and Uhlendorff, 2006; Greene, 2006):

$$\log L = \sum_{i=1}^{N} \log \frac{1}{R} \sum_{r=1}^{R} \left[(1 - w_i) + w_i \left(\frac{\exp(\beta_j' Z_i + \omega_{ir})}{1 + \exp(\beta_j' Z_i + \omega_{ir})} \right) \right] \Phi\left[(2w_i - 1)(X_i' \gamma_i + \omega_{ir}) \right] \tag{7}$$

where R is the number of random draws from the standard normal population. The unobserved heterogeneity ω is assumed to be identically and independently distributed over the youth and follows a multivariate normal distribution with mean ω_μ and variance-covariance matrix $\mathbf{W}, \omega \sim f(\omega_\mu, W)$. We estimate simultaneously the parameters of our probit-selection multinomial logit model with unobserved heterogeneity using simulated maximum likelihood (Terza, 2002).

3.2 Models of economic effects of skill and educational mismatches

One of the key empirical questions in the mismatch literature is to understand the extent to which mismatched workers fare in the labor markets compared with their peers who are well matched in terms of skills and education (Duncan and Hoffman, 1981; Groot, 1993; Kiker et al., 1997; Hartog, 2000; Bauer, 2002; Quinn and Rubb, 2006). The outcomes of interest are generally the wage, the degree of job satisfaction, on-job search, and unemployment spell effects of job mismatch. However, much of the empirical literature is applied to developed countries and does not explicitly target youth in African countries. To the best of our knowledge, this paper is the first empirical exercise to fill this knowledge gap. The following section presents our empirical strategy to measure each of the abovementioned potential effects of mismatch.

3.2.1 Model of wage effects

Human capital and job competition theories suggest that job mismatch is a purely temporary disequilibrium in the labor markets and that the rate of returns to education is uncorrelated with whether or not a worker is well matched to his or her job (Becker, 1975) and that there are no returns to over- and undereducation (Thurow, 1975). For these assumptions to hold, both theories assume that firms are able to adjust, automatically and without cost, their production technology in response to any change in the quality and quantity of labor supply (Dolton and Vignoles, 2000). However, as summarized by Bauer (2002), empirical studies consistently find, at least in developed countries, that overeducated workers earn less on average than individuals in jobs with adequate level of education and that the returns to years of undereducation are often negative.

To estimate the wage effects of mismatch in the labor markets, the standard Mincerian model is extended following the Verdugo and Verdugo model (1989). They proposed the use of two dummy variables for being overeducated ($overeduc_i$) and undereducated ($undereduc_i$) and controlled for the actual years of education attained E_i so that the extended Mincerian model of the wage equation (W_i) under educational mismatch is then written as:

$$\ln W_i = \beta_0 + \beta_1 E_i + \beta_r overeduc_i + \beta_u undereduc_i + X_i \delta_i + \varepsilon_i \tag{8}$$

where β_1 captures the returns to years of actual education; and β_r and β_u measure the wage effects of overeducation and undereducation, respectively; X_i is a vector of individual socioeconomic and job characteristics; and ε_i is the error term. $overeduc_i$ and $undereduc_i$ take the values 1 if the worker is overeducated or undereducated, respectively, and 0 otherwise. In this case, if wages are solely determined by the actual level of education of workers E_i, then $\beta_r = \beta_u = 0$, and the human capital theory will hold. If instead, wages are determined by a required level of education, then any additional year of education exceeding the required level will become unproductive and the overeducated (undereducated) worker will earn less (more) than a similar worker with adequate level of education, implying that $\beta_r < 0$ and $\beta_u > 0$.

However, as shown in the previous sections, skill and educational mismatches are not perfectly correlated and being skill-matched does not necessarily also imply being education-matched (Allen and van der Velden, 2001; Allen and De Weert, 2007; Mavromaras et al., 2010). To ascertain to what extent skill mismatch also affects wages of employed youth, we augment equation (8) by the measures of youth self-assessment of overskilling ($overskill_i$) and underskilling ($underskill_i$), which take the value 1 if the youth considers him/herself overskilled or underskilled, respectively, and 0 otherwise. Hence, our working empirical model of the wage effects of job mismatch becomes:

$$\ln W_i = \beta_0 + \beta_1 E_i + \beta_o^e overeduc_i + \beta_u^e undereduc_i + X_i\delta_i + \beta_o^s overskill_i + \beta_u^s underskill_i + \varepsilon_i \quad (9)$$

where the superscripts e and s on the parameters β refer to education and skill mismatches, respectively. By including both types of job mismatch, we are able to identify which one has stronger effects on wages.

Equation (9) is traditionally estimated using standard OLS techniques. However, OLS estimates are biased if the error terms in (9) are correlated with the components of education or skill mismatch, which is likely to be the case (Card, 1999; Ashenfelter et al., 1999; Leuven and Oosterbeek, 2011). As a result, the estimated coefficients of both skill and educational mismatches could be reporting the effects of other unobserved factors that differ by the type of mismatch, leading to either a positive or negative bias, depending on the correlation between ε_i and mismatch variables. The model in equation (9) therefore suffers from both sample selection and endogeneity problems to be corrected for.

To correct for both sample selection and endogeneity problems, we apply the following estimation procedure proposed by Wooldridge (2010). In the first step, we obtain the inverse Mills ratio (λ_i) from the probit model of the likelihood of being employed or not, using the same set of variables as those in equation (4). In the second step, we use the subsample of employed youth and estimate equation (9) by the IV-2SLS approach after incorporating λ_i. A classical test of no sample selection problem can be performed on the estimated coefficient of λ_i. In case of evidence of sample selection bias, the standard errors should be corrected for first-stage estimation. For the 2SLS method, given that we have 5 potential endogenous variables in equation (9)[9], we need at least one instrument per endogenous variable to identify the models. These instruments should however fulfill two conditions: relevance (high correlation between the instrument and the endogenous regressor) and exogeneity (absence of correlation between the instrument and the error term in the main regression). The choice of the instruments is generally determined by data availability in the surveys and the specific objectives of the study. As potential instruments, we decompose the education of the employed youth's father and mother into three components, following the same procedure applied to define our educational mismatch variable: parent's required education (1 if the parent's highest level of education matches his/her job requirements and 0 otherwise), parent's overeducation (1 if s/he is overeducated and 0 otherwise) and parent's undereducation (1 if s/he is

[9] $E_i, overeduc_i, undereduc_i, overskill_i$ and $underskill_i$

overeducated and 0 otherwise). We applied different tests (overidentification, underidentification and weak instruments) to assess the validity of our selected instruments.

3.2.2 Model of job satisfaction effects

Similar to the above wage model, it is also relevant to investigate to what extent the prevalence of skill and/or educational mismatches affect job satisfaction of African youth. This is particularly important for youth because empirical studies have suggested that job dissatisfaction due to mismatch tends to influence both the productivity of the worker and the worker's likelihood of job change (Battu et al., 1999, 2000; Allen and van der Velden, 2001; Amador et al., 2012). In the standard economic theory, job satisfaction will depend negatively on a worker's effort and positively on wages, but will also depend on other job- and worker-specific characteristics (Sloane and Williams, 1996; Souza-Poza and Souza-Poza, 2000; Hamermesh, 2001; Florit and Lladosa, 2007). Studies that have included a measure of mismatch in job satisfaction models generally find a significant correlation between skill and/or educational mismatches and the level of job satisfaction. In particular, Battu et al. (1999) found a negative effect of overeducation on both wages and job satisfaction, similar to the results of Johnson and Johnson (2002) and Florit and Lladosa (2007) on the effect of skill mismatches on job satisfaction. However, using European data, Allen and van der Velden (2001) found instead that skill mismatch has a stronger effect on job satisfaction than educational mismatch.

In the STWT datasets, employed youth were asked the following question: "To what extent are you satisfie*d with your current job?"* with the potential rank responses ranging from the scale 1 (*very satisfied*) to 6 (*very unsatisfied*)[10]. Due the ordered nature of the job satisfaction scores in the surveys, we apply an ordered probit model to estimate the effects of mismatch on job satisfaction and account for the endogeneity of mismatch variables. To reduce the dimensionality of our dependent variable, we merged scales 2 and 3 on the one hand and 4 and 5 on the other to get a 4-scale ordered score: 1=*Very unsatisfied* (base category)*;* 2=*Unsatisfied*; 3=*Satisfied*; 4=*Very satisfied*[11]. The empirical model of job satisfaction is represented as follows:

[10] The scales are 1=*Very satisfied;* 2=*Quite satisfied;* 3=*Satisfied*; 4=*Quite unsatisfied*; 5=*Unsatisfied*; and 6=*Very unsatisfied.*

[11] We remove from the estimation 179 observations where the youth declared they were "neither satisfied nor unsatisfied".

$$JS_i^* = \beta_0 + \boldsymbol{\beta_1}\mathbf{M_i} + \boldsymbol{\beta_2}\mathbf{X_i} + \varepsilon_i, \quad \text{with} \quad JS_i = j \;\; if \;\; \tau_{j-1} < JS_i^* < \tau_j, \quad j = 1, \dots, 4 \tag{10}$$

where JS_i^* is a latent variable because the econometrician only observes an indicator variable JS_i in which the youth has evaluated his/her level of job satisfaction by an ordered scale j. $\mathbf{M_i}$ is a vector of endogenous mismatch variables ($overeduc_i, undereduc_i, overskill_i$ and $underskill_i$) defined previously. $\mathbf{X_i}$ is a vector of control variables related to personal and employment characteristics. In particular, in addition to personal and employment characteristics used in equation (1), we also include in $\mathbf{X_i}$ hourly wage, duration of unemployment before current job (1 if more than 1 year; 0, otherwise), employment benefits (1 if the youth received employment benefits in current job, 0, otherwise; and the total number of employment benefits), youth's goal in life[12], job training (1 if the youth has received a training over the last 12 months to improve current work; 0, otherwise), underemployment (1 if the youth feels underemployed; 0, otherwise)[13] and trade union (1 if the youth is member of a trade or labor union; 0, otherwise). ε_i is an error term assumed normally distributed with $\varepsilon_i \sim N(0,1)$. The instruments for $\mathbf{M_i}$ are the same as those used in the wage equation. Equation (10) is estimated using the IV-ordered probit model corrected for sample selection bias (Roodman, 2011).

3.2.3 Model of on-job search effects

Economic theory predicts that workers who are currently mismatched in their job are more likely to search alternative jobs than better matched peers (Allen and van der Velden, 2001; Cahuc et al., 2006; Dolado et al., 2009; DeLoach and Kurt, 2018). Allen and van der Velden (2001) found for instance that European workers who report skill underutilization in their job were more likely to look for alternative jobs than those who reported no underutilization. In our surveys, employed youth were asked the following question: *"In the last month, did you apply for any other jobs to replace your current job?"* with a yes-or-no answer. To test the job-search theory under mismatch in the context of African youth, we estimate a simple endogenous job-search model using a IV-probit specification.

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[12] A categorical variable: 1 if the main objective of the youth in life is to "Find a job"; 2, "Have a professional success"; 3, "Contribute to society"; 4, "Earn a lot of money"; 5, "Raise a good family"; or 6, "Other objectives".
[13] The underemployment variable was constructed from the following survey question: "*Last week, would you have worked more overhours if they would have been remunerated?*" The worker is then classified as *underemployed* if s/he replied by "Yes" to the question.

$$D_i = \beta_0 + \boldsymbol{\beta_1}\mathbf{M_i} + \boldsymbol{\beta_2}\mathbf{X_i} + \varepsilon_i, \tag{11}$$

The dependent variable D_i takes the values 1 if the employed youth has applied for a job and 0 otherwise. The other variables have been previously defined.

4. Results and discussions

4.1. Drivers of skill and educational mismatches

Table 4.1 reports the average marginal effects of the multinomial logit models for the likelihood of being job mismatched when accounting for sample selection bias and unobserved heterogeneity. The model is estimated separately for skill and educational mismatches. Estimation results show that most covariates significantly affect the likelihood of being job mismatched in the selected countries. Female youth are more likely to feel overskilled in their job than males. Specifically, being an employed female youth is significantly associated with an average 1% increase in the likelihood of overskilling. However, similar to findings by Chevalier (2003) and Chevalier and Lindley (2009), the probability of both overeducation and undereducation is not gender related.

The level of education of employed youth significantly impacts the likelihood of being skill mismatched. The average marginal effects of overskilling (underskilling) are increasing (decreasing) as we move from lower to higher educational attainment. Youth with tertiary education have a 31.6% more chance of feeling overskilled and a 22.7% less chance of being underskilled than youth with lower educational levels. Results also highlight the heterogeneous effects of the fields of study during schooling on the probabilities of skill or educational mismatches once employed. Self-assessed overskilling is highly probable for youth who followed services curriculum, whereas the risk of underskilling is significantly decreasing for all the fields of study. Importantly, however, although the subject of study during schooling is an important determinant in finding a job, our results show that it does not protect African youth against the likelihood of being either overeducated or undereducated. Youth who studied Arts & Literature have a significantly lower risk of being overeducated, while general programs, engineering, health and services curricula reduce the probability of undereducation. Importantly and contrary to job search and career mobility theories, the likelihood of being job mismatched does not decline with the age of the employed youth in Africa. In fact, relative to youth aged 15–19 (the youngest cohort in the surveys), the probability of being overskilled or overeducated is 1.2% and 3.7% higher for employed youth aged 20–24 years old. It increases further to 3% and 8.9%, respectively, for those in the 25–29 age bracket. A similar pattern is observed for the marginal effects of being underskilled or undereducated. This implies that the probability of finding a better job match in the labor markets does not improve as the youth move from younger to older cohorts and that job mismatch might be a rather persistent phenomenon for employed African youth (see Section 5.1 below). Another potential explanation is the existence of important labor market inefficiencies and failures in Africa where search and information costs are often prohibitive. In such a situation, not only does it take time for youth entering the labor market to find a better job match but also this mismatch is likely to become more prevalent over time.

There is also a significant relationship between parents' education and their children's job mismatch status. Parameter estimates reveal that youth coming from more educated families have a lower chance of being job mismatched (Ordine and Rose, 2009). Indeed, employed youth with tertiary educated parents are less likely to be either over- or underskilled and therefore are more likely to be in a well-matched job. On the other side, parents' education has a significantly positive (negative) effect on the risk of overeducation (undereducation) of their young children only from the secondary level.

In terms of employment characteristics, several interesting findings emerge from Table 4.1. First, relative to other employment statuses, self-employed and wage-employed workers and employers are less likely to feel underskilled, with the risk being lower for employers. Salary workers have a 1.9% lower chance of being overeducated compared with other categories of workers. This finding can be explained by the fact that most self-employed youth are in the informal sector, where low and unskilled jobs prevail (Herrera and Merceron, 2013).

Second, holding other characteristics constant, we expect youth working in higher occupation levels[14] to experience less skill deficits than youth in lower-skill occupations[15]. Our results partially confirm this theoretical prediction. Youth employed as managers and professionals have a better chance of having the appropriate skills for their jobs but unexpectedly, they are less likely to be overeducated than undereducated, tending to confirm that skill and educational mismatches are not necessarily complementary.

Third, results show that better skilled youth are more likely to work in secondary and tertiary sectors than in agriculture.

[14] Managers, professionals, technicians and associate professionals.

[15] Support, sales, trade workers, elementary occupations, etc.

Table 4.1: Multinomial logit estimates for the likelihood of being job mismatched corrected for sample selection and unobserved heterogeneity (Average marginal effects)

	Skill mismatch		Educational mismatch	
	Overskilled	Underskilled	Overeducated	Undereducated
Gender (1 if female)	0.010	0.003	0.003	-0.009
	(0.005)**	(0.005)	(0.003)	(0.006)
Marital status (1 if married)	-0.018	0.016	-0.015	0.044
	(0.006)***	(0.007)**	(0.004)***	(0.007)***
Education (ref: No education)				
Primary education	0.038	-0.089	-	-
	(0.005)***	(0.008)***		
Secondary education	0.216	-0.182	-	-
	(0.008)***	(0.009)***		
Tertiary education	0.316	-0.227	-	-
	(0.016)***	(0.016)***		
Field of study (ref: Other)				
General programs	0.021	-0.075	-0.009	-0.074
	(0.013)	(0.014)***	(0.020)	(0.029)**
Education sciences	-0.041	-0.074	0.002	-0.064
	(0.018)**	(0.024)***	(0.027)	(0.048)
Arts & Literature	0.057	-0.056	-0.087	-0.273
	(0.047)	(0.064)	(0.002)***	(0.033)
Social sciences	0.030	-0.096	0.015	0.029
	(0.019)	(0.029)***	(0.020)	(0.020)
Science, Math, ICT	-0.002	-0.063	-0.026	-0.033
	(0.026)	(0.038)*	(0.021)	(0.051)
Engineering	-0.015	-0.085	0.022	-0.123
	(0.022)	(0.036)**	(0.020)	(0.048)***
Agriculture	-0.034	-0.137	-0.010	-0.019
	(0.036)	(0.055)**	(0.041)	(0.075)
Health	0.003	-0.064	0.070	-0.178
	(0.019)	(0.026)**	(0.058)	(0.107)*
Services	0.128	-0.099	-0.022	-0.131
	(0.038)***	(0.040)**	(0.023)	(0.057)**
Age groups (Ref: 15–29 years)				
20–24 years	0.012	-0.008	0.037	-0.145
	(0.006)**	(0.007)	(0.003)***	(0.007)***
25–29 years	0.030	-0.031	0.089	-0.235
	(0.008)***	(0.009)***	(0.005)***	(0.008)***
Relation with the head (1 if head)	-0.022	0.007	-0.002	-0.029
	(0.007)***	(0.008)	(0.005)	(0.008)***
Location (1 if rural)	-0.015	0.010	-0.005	0.033
	(0.005)***	(0.006)	(0.003)	(0.006)***
Father's education (1 if no education)				
Primary education	0.003	-0.015	0.007	-0.023
	(0.010)	(0.011)	(0.007)	(0.011)**
Secondary education	0.008	-0.001	0.044	-0.133
	(0.011)	(0.012)	(0.007)***	(0.012)***
Tertiary education	-0.040	-0.043	0.084	-0.159
	(0.013)***	(0.020)***	(0.011)***	(0.019)***
ISCO skill level of father's work (Ref: Unskilled work)				
Skilled work	-0.012	0.000	0.013	-0.054
	(0.010)	(0.014)	(0.006)**	(0.013)***
Semi-skilled work	-0.023	0.010	-0.001	-0.005
	(0.008)***	(0.010)	(0.004)	(0.009)
Mother's education (Ref: No education)				
Primary education	0.004	0.015	0.003	-0.004
	(0.013)	(0.012)	(0.008)	(0.013)
Secondary education	0.003	-0.014	0.026	-0.083
	(0.013)	(0.014)	(0.009)***	(0.014)***
Tertiary education	-0.011	-0.007	0.065	-0.207
	(0.021)	(0.037)	(0.019)***	(0.031)***
ISCO skill level of mother's work (Ref: Unskilled worker)				
Skilled worker	0.015	-0.000	0.043	-0.048
	(0.009)*	(0.017)	(0.006)***	(0.012)***
Semi-skilled worker	0.022	-0.037	0.007	-0.014
	(0.007)***	(0.008)***	(0.004)*	(0.009)
Employment status (Ref: Other)				
Wage employment	0.011	-0.059	-0.019	-0.004
	(0.008)	(0.011)***	(0.005)***	(0.010)
Self-employment	0.005	-0.034	-0.006	-0.001
	(0.007)	(0.007)***	(0.005)	(0.008)

Employer	-0.007	-0.069	-0.000	-0.014
	(0.013)	(0.014)***	(0.009)	(0.015)
ISCO skill-level of youth work (Ref: Unskilled worker)				
Skilled worker	-0.128	-0.060	-0.391	0.643
	(0.009)***	(0.015)***	(0.008)***	(0.010)***
Semi-skilled worker	-0.032	0.012	-0.328	0.394
	(0.007)***	(0.008)	(0.008)***	(0.007)***
Sector (Ref: Agriculture)				
Industry	-0.026	-0.036	0.002	-0.022
	(0.008)***	(0.009)***	(0.005)	(0.009)**
Services	-0.012	-0.038	0.029	0.064
	(0.006)*	(0.007)***	(0.004)***	(0.007)***
Type of contract (1 if written contract)	-0.059	-0.060	0.038	-0.113
	(0.012)***	(0.018)***	(0.007)***	(0.014)***
Duration of contract (1 if less than 1 year)	0.038	0.006	-0.004	0.011
	(0.010)***	(0.014)	(0.006)	(0.013)
Work experience	-0.008	0.004	-0.014	0.033
	(0.000)***	(0.000)***	(0.001)***	(0.001)***
Firm size (Ref: Less than 10 workers)				
10–49	-0.043	0.032	0.034	-0.043
	(0.008)***	(0.014)**	(0.007)***	(0.012)***
50–499	-0.065	0.032	0.022	-0.055
	(0.011)***	(0.024)	(0.009)**	(0.018)***
More than 500	-0.071	-0.031	0.050	-0.043
	(0.013)***	(0.038)	(0.013)***	(0.021)**
Country dummies	YES	YES	YES	YES
Year dummies	YES	YES	YES	YES
Predicted probabilities	0.18	0.28	0.09	0.56
Observations	24,003	24,003	21,180	21,180

Note: Robust standard errors into brackets. (*), (**), and (***) refer to statistically significant coefficients at least at the 10%, 5% and 1% level, respectively.

Being employed in the industry and services sectors decreases by 2.6 and 1.3%, respectively, the likelihood of feeling overskilled and by 3.6% and 3.8%, respectively, the probability of being underskilled. This is because not only do a larger proportion of firms in the industry and services sectors operate in the formal sector but they also face fiercer competition, which requires well-qualified workers. In that context, they are more likely to develop better screening and recruitment processes, which increases the chances of identifying well-matched workers. However, tertiary sector workers are more likely to be both overeducated and undereducated, while secondary sector workers have a lower probability of being undereducated.

Finally, the size of the firm where youth are employed significantly affects the probabilities of both skill and educational mismatches. In particular, the larger the firm size, the lower the likelihood of being overskilled. The average marginal effects of being overskilled range from –4.3% when the number of workers is 10–49 to –6.5% for 50–499 workers and –7.1% for 500 workers and more. This finding can be partly explained by asymmetric and imperfect information in labor markets, where larger firms have more resources and better selection processes to spot and dismiss mismatched workers. It is also possible that mis-skilled youth self-select themselves out of employment in large firms due to very restrictive job requirements. Alternatively, larger firms generally have sufficient resources to offer better salaries and employment benefits that attract skilled workers. In terms of educational mismatch, findings show that larger firms are more likely to have both better-skilled and overeducated youth. Indeed, working in a firm of 10–49 workers increases the likelihood of being overeducated by 3.4% but reduces by 4.3% the risk of being undereducated.

4.2. Wage effects of skill and educational mismatches

Table 4.2 reports the estimation results of the extended Mincerian model to assess whether job mismatch leads to a wage premium or instead to a wage penalty for employed youth. In Table 4.2, we report the estimation results for 4 different models: a simple pooled OLS in model 1, a model with educational mismatch corrected for sample selection bias but without endogeneity (model 2), a model with skill and educational mismatches without endogeneity but corrected for sample selection bias (model 3) and a full model corrected for both endogeneity problems and sample selection bias (model 4). We focus our discussion on model 4 because coefficients in models 1 and 3 are likely to be biased due to endogeneity problems. All standard tests of the validity and relevance of our excluded instruments support our choice of instruments. In particular, the statistically insignificant Hansen J test of overidentifying restrictions concludes that our instruments are valid and we cannot therefore reject the null hypothesis of instrument exogeneity. In addition, the Montiel-Pflueger robust weak instrument test rejects at 5% the null hypothesis of weak instruments for our 2SLS estimation.

After controlling for personal and job characteristics, country and year effects, results in model 4 strongly reject the predictions of the human capital and job competition theories that only actual education is important in wage determination (i.e. $\beta_o^e = \beta_u^e = 0$ and $\beta_o^e = \beta_u^e = \beta_o^s = \beta_u^s = 0$). In line with the assignment theory (Sattinger (1993), our findings reveal that the returns to years of actual education are significantly higher than the wage effects associated with educational mismatch, with each additional year of actual education estimated to increase the expected wage by 0.61%. Furthermore, estimation results from model 4 suggest that overeducated youth earn on average 17.9% less and undereducated 44.8% more than employed youth with the same level of education who work in matched jobs, confirming the theoretical predictions that overeducation is associated with a wage penalty and undereducation with a wage premium. Herrera and Merceron (2013) for African countries, Santos (1995) for Portugal and Bauer (2002) for Germany found similar results. As explained by Hartog (2000), the negative effect of the overeducation coefficient may imply that overeducated workers are likely employed in lower-level jobs than youth without overeducation. Indeed, descriptive statistics reported in Table 2.2 reveal that none of the overeducated youth are employed in skilled jobs or hold managerial and professional positions in their work. Finally, only overskilling appears to affect wage levels of employed youth: being overskilled generates a wage penalty of 6.7% compared with other categories of workers.

Table 4.2: Heckman-corrected Mincerian earning equation: Augmented Verdugo and Verdugo model

	Model 1	Model 2	Model 3	Model 4
Years of actual education	0. 134	0.131	0.202	0.609
	(0.028)***	(0.028)***	(0.029)***	(0.172)***
Overeducation (1 if overeducated)	-0.070	-0.070	-0.100	-0.179
	(0.049)	(0.047)	(0.049)**	(0.060)***
Undereducation (1 if undereducated)	0.134	0.133	0.164	0.448
	(0.037)***	(0.040)***	(0.043)***	(0.126)***
Overskilling (1 if overskilled)			-0.078	-0.067
			(0.038)**	(0.038)*
Underskilling (1 if underskilled)			-0.055	0.038
			(0.051)	(0.069)
$\boldsymbol{R^2}$	0.225			0.311
$\boldsymbol{LR\ test\ (\rho = 0)}$	-	0.51	0.76	-
		(0.477)	(0.384)	
$\boldsymbol{H_0: \beta_o^e = \beta_u^e = 0}$	6.91	14.97	21.32	15.05
	(0.001)***	(0.001)***	(0.000)***	(0.001)***
$\boldsymbol{H_0: \beta_o^e = \beta_u^e = \beta_o^s = \beta_u^s = 0}$			33.16	21.30
			(0.000)***	(0.001)***
Personal and job characteristics	YES	YES	YES	YES
Country dummies	YES	YES	YES	YES
Year dummies	YES	YES	YES	YES
Observations	22,976	22,976	22,976	22,976

Note: In model 4: Anderson canon. corr. LR statistic for under-identification test: 206.766 (p = 0.000). Sargan statistic for overidentification test of all instruments: 7.250 (p = 0.202). Montiel-Pflueger robust weak instrument test: 37.651 (p = 0.05). Robust standard errors in models 1–3 and bootstrapped standard errors in model 4 with 10,000 replications. (*), (**), and (***) refer to statistically significant coefficients at least at 10%, 5% and 1% level, respectively.

4.3. Jobs satisfaction effects

Table 4.3 reports the estimation results of the effects of skill and educational mismatches using an ordered probit model corrected for sample selection bias and endogeneity problem. As expected, skill and educational mismatches are significant predictors of the degree of job satisfaction of employed youth when we control for education level, job attributes and personal characteristics. In particular, our results suggest that, in terms of educational mismatch, only undereducation in a current job significantly affects the probability of job satisfaction, and its effects are heterogeneous, depending on the extent of job satisfaction.

Undereducated youth are more likely to be dissatisfied with their current job and the effect is more pronounced as the degree of job satisfaction increases. Indeed, Table 4.3 indicates that the average marginal effects of undereducation are positive for job dissatisfaction (0.045 for *very unsatisfied* and 0.037 for *unsatisfied* youth) and negative for job satisfaction (–0.014 for *satisfied* and –0.068 for *very satisfied* youth). A potential explanation of this result is that youth who have education deficits compared with their peers may feel more deprived and develop an inferiority complex that could negatively affect their utility. Alternatively, youth who have the required education are more satisfied as they consider that their educational investment has paid off as expected (Florit and Lladosa, 2007).

However, our results show that skill mismatches are better drivers of job satisfaction of youth than educational mismatches because both overskilling and underskilling reduce the probabilities of job satisfaction. Overskilled youth have 3.4% less chance of being satisfied with their current job while satisfied youth are 1.8% less likely to be underskilled. Similar findings of the effects of job mismatch have been reported by Green and Zhu (2008) for Britain, Amador et al. (2012) for Spain, Allen and van der Velden (2001) for 11 European countries and Japan, McGuinness and Sloane (2011) for U.K. graduates and Sánchez-Sánchez and McGuinness (2015) for 13 European countries. When youth occupy jobs that they feel underutilize their competences and skills, they become less satisfied because, extrinsically, they might foresee few career opportunities and, intrinsically, they might feel their competences are not as appreciated or leveraged as they should be, leading to resignation to their work condition (Peiro et al., 2010). The decreased satisfaction of underskilled youth could be instead explained by the fact that they might work under considerable pressure as they consistently try to keep up with the skill requirements of a job for which they experience more or less important gaps. In a labor market characterized by high unemployment rates, like in most African countries, and therefore fierce competition for few available positions, underskilled youth might then dread being dismissed due to insufficient skills.

Finally, our observation that undereducated youth have a lower likelihood of job satisfaction while at the same enjoying a wage premium (see Table 4.2) suggests the existence of a sort of trade-off between earnings and other nonmonetary aspects of their work, the lack of satisfaction being somewhat offset by higher earnings. This trade-off does not seem to exist for overskilled youth because they suffer from the double burden of wage penalty and job dissatisfaction. These results therefore suggest that both skill and educational mismatches should be urgently addressed because they affect both wages and job satisfaction of employed youth.

Table 4.3: Average marginal effects of skill and educational mismatches on job satisfaction: Ordered Probit model with sample selection and endogeneity

	Degree of job satisfaction			
	Very unsatisfied	Unsatisfied	Satisfied	Very satisfied
Hourly wage	-0.010	-0.009	0.003	0.016
	(0.002)***	(0.002)***	(0.001)***	(0.003)***
Overeducation (1 if Overeducated)	-0.029	-0.024	0.009	0.044
	(0.038)	(0.032)	(0.012)	(0.058)
Undereducation (1 if Undereducated)	0.045	0.037	-0.014	-0.068
	(0.015)***	(0.012)***	(0.005)***	(0.023)***
Overskilling (1 if Overskilled)	0.112	0.092	-0.034	-0.169
	(0.007)***	(0.005)***	(0.004)***	(0.010)***
Underskilling (1 if Underskilled)	0.061	0.049	-0.018	-0.091
	(0.008)***	(0.007)***	(0.003)***	(0.012)***
Personal and job characteristics	YES	YES	YES	YES
Country dummies	YES	YES	YES	YES
Year dummies	YES	YES	YES	YES
Observations	5,649	5,649	5,649	5,649

Note: (*), (**), and (***) refer to statistically significant coefficients at least at 10%, 5% and 1% level, respectively. The marginal effects of the dummy variables show the discrete change from 0 to 1.

4.4. On-job search effects

If skill and educational mismatches affect both the wages and the degree of satisfaction of employed youth, do they also have real behavioral consequences in the labor markets, for instance pushing youth to look for alternative employment opportunities? Table 4.4 answers that question by reporting the results of three different specifications: a model with skill and educational mismatches without correction for endogeneity and sample selection bias (model 1), a model without endogeneity but corrected for sample selection bias (model 2), and a model corrected for both endogeneity and sample selection bias.

Consistent with predictions of on-job search (OSJ) models (Burdett, 1978; Deloach and Kurt, 2018), our empirical evidence suggests that mismatched youth are more likely to search for alternative jobs than their better-matched peers, irrespective of the estimation method chosen. Skill-mismatched and overeducated youth are more likely to look for other jobs than are undereducated youth. Specifically, after controlling for other characteristics, we find that an additional year of overeducation increases by 0.18% the likelihood of an employed youth searching for other jobs while overskilled youth are 0.31% more likely to apply for other jobs to replace their current job.

Possible explanations for these behavioral consequences of job mismatch might however diverge, depending on the type of job mismatch considered. For instance, overeducated youth might be frustrated that their investment in education is not paying off as expected compared with their peers, in particular if salaries and benefits in their current job are determined by the required rather than the actual level of education. In addition, according to the job-searching theories of Johnson (1978) and Jovanovic (1979), asymmetric information might prevent workers from perfectly foreseeing the quality of the job match and they may therefore accept jobs that turn out not to match their education or skills. Finally, it is plausible that overeducated and overskilled youth might fear the depreciation of their human capital because of non-use in their current job, resulting in declines in productivity (Rubb, 2006). Consequently, these mismatched youth will be more willing to seek alternative positions until they find a better job match (Frei and Sousa-Poza, 2012). This explanation is also confirmed in the surveys: when asked why they would like to change their current job, 21.9% of overskilled youth responded that they wanted to use their skills efficiently, compared with only 4.6% of underskilled.

Undereducated youth, on the other hand, are less likely to search for other jobs because, despite being short on education, they might feel that they have been lucky to even have a job. This explanation is plausible because the prospect of unemployment is daunting and the chances of getting a skill-matched or even just a decent job are often low in most African countries. Another potential explanation is simply that undereducated youth might be working in sectors that include a significant component of specialized vocational and on-the-job training that may substitute for the formal education. This argument is supported by the fact that among the undereducated youth in the sample, 56% felt that they have the appropriate skills to perform their jobs and 9% of them even described themselves as overskilled. Finally, the explanation used to explain job dissatisfaction of underskilled is also valid here for job search: the fear of losing their job due to the lack of required skills might push underskilled youth to search for better matched jobs.

Table 4.4: Average marginal effects of skill and educational mismatches on the likelihood of job search: IV probit model with sample selection and endogeneity

	Model 1	Model 2	Model 3
Years of overeducation	0.007	0.013	0.178
	(0.003)**	(0.003)***	(0.083)**
Years of undereducation	-0.002	-0.007	-0.024
	(0.003)	(0.002)***	(0.007)***
Over-skilling (1 if overskilled)	0.102	0.116	0.308
	(0.013)***	(0.014)***	(0.089)***
Under-skilling (1 if underskilled)	0.025	0.029	0.120
	(0.018)	(0.019)	(0.070)*
Predicated probability: $\textbf{Prob}\ (\boldsymbol{D_i} = \mathbf{1})$	0.228	0.237	0.234
Personal and job characteristics	YES	YES	YES
Country dummies	YES	YES	YES
Year dummies	YES	YES	YES

Observations	5,249	5,249	5,249

Note: In model 3: Wald test of exogeneity (corr = 0): chi2(1) = 2.31, Prob > chi2 = 0.1288. Robust standard errors in models 1 and 2 and bootstrapped standard errors in model 3 with 10,000 replications. (*), (**), and (***) refer to statistically significant coefficients at least at 10%, 5% and 1% level, respectively. [ ] refers to *p*-values.

5. Model extensions

5.1. Persistence of mismatches over time

Previous sections have shown that skill and educational mismatches are pervasive among African youth. If job mismatches are only temporary disequilibrium in the labor markets, then short-term government interventions may suffice to address the problem. If instead, job mismatch is more persistent over time, then more structural policy actions will be needed. To understand whether skill and education mismatches are transitory phenomenon or rather a more persistent state in Africa, we computed transition probability matrices of employed youth.

In the absence of longitudinal data, we constructed pseudo-panel data of employed youth for each of the two survey years and excluded countries with only one survey round (Congo and Tanzania) [16]. The pseudo-panel approach has been widely applied in the econometric literature to estimate mobility across different states over time, such as mobility across employment status, occupations and poverty dynamics, with the assumption that individuals within the same cohort not only share the same observable characteristics but also have the same likelihood of being well matched or mismatched in the labor markets (Lanjouw et al., 2009; Verbeek and Nijman, 1992; Deaton, 1985). According to Deaton (1985) and Verbeek and Nijman (1992), a *cohort* represents a group of individuals assumed to be homogeneous and who are followed over the observed period so that the dynamism of the phenomenon under study is evaluated for each cohort. Despite its drawbacks, the cohort approach has gained popularity among developing countries' researchers due to the lack of long-panel data.

Before constructing our pseudo panel dataset and ensuring its reliability, two important issues have to be addressed: temporal cohort stability and measurement error bias. The first issue consists of establishing cohort stability over time. To ensure stability, Deaton (1985) proposes the use of time-invariant characteristics when creating cohorts. The underlying idea

[16] This means for the remaining 8 countries, there is a 2-year gap between the 2 surveys: between 2012 and 2014 for Benin, Liberia, Togo, Zambia, Egypt and Malawi and between 2013 and 2015 for Madagascar and Uganda.

is that the more time-invariant variables we include when constructing cohorts, the closer the characteristics of the constructed pseudo panel will become to those from genuine panel data. In the present study, we defined youth cohorts using the country of residence, the birth generation[17], the gender and the highest level of education attained by employed youth. Such choice represents an important trade-off between the need to have a sufficient number of individuals per cohort and the desire to have a large number of cohorts. Indeed, the greater the number of cohorts, the fewer the number of observations per cohort, therefore the greater the potential error in estimating the cohort mean.

The measurement error bias represents the second important problem to be addressed because it affects the consistency of the pseudo panel estimators. The bias occurs when the sample means deviate from the true cohort means in the population, resulting in biased OLS estimation. The acuity of this problem will mainly depend on the sample size and the skewness of the mean. Hence, the smaller the sample size (number of observations per cohort and/or number of cohorts) and the more skewed the mean by extreme numbers, the greater the risk of measurement error. Two solutions are generally proposed to deal with this problem: the use of error-in-variable estimators or a within estimator. However, according to Verbeek and Nijman (1992), the condition to ignore the measurement error problem is to construct cohorts with sufficient number of observations. In our study, only cohorts with at least 50 youth have been considered for the construction of transition probability matrices, resulting in 579 cohorts for skill mismatch and 451 cohorts for skill and educational mismatch, respectively.

To document movements into and out of job mismatch of employed youth, Table 5.1 gives the transition probabilities of being job (mis)matched in year *t* given the youth cohort's state in year *t*–1 for the pooled sample. As shown, job mismatch among employed youth appears to be a persistent phenomenon in Africa. However, three key differences can be observed between different types of (mis)matched youth cohorts. First, skill-matched cohorts have lower chances to remain well-matched after 2 years compared with youth cohorts with the required education level. In particular, the probability of a skill-matched cohort to remain well-matched is only 34.9%, compared with 41% for youth cohorts with the required education. Second, for all types of job mismatch, state dependence is more pronounced for educational mismatch than skill mismatch. For instance, year *t*'s overeducation risk among the overeducated in year *t*–1 is 4.4 percentage points higher than for overskilled and as much as

[17] We constructed 5 birth generations using a 5-year interval: youth born between 1977 and 1981 (529 youth); between 1982 and 1986 (5,873 youth); between 1987 and 1991 (9,779 youth); between 1992 and 1996 (9,720 youth); and between 1997 and 2000 (4,620 youth).

18.43 percentage points higher for undereducated than for underskilled. Finally, skill mismatched cohorts are more likely to transition to better job matches than youth cohorts with inadequate education. Youth cohorts who started off overskilled in year *t*–1 have 39.1% more chance of feeling well-matched in year *t*, and those who started off underskilled have 41.5% chance. These probabilities decline to 30% and 38.9% for overeducated and undereducated, respectively.

Table 5.1: Transition probability matrices of youth cohorts by job mismatch status

		Part 1: Skill mismatch status		
		Year *t*		
		Well-matched	Overskilled	Underskilled
Year *t*-1	Well-matched	**34.91**	32.55	32.55
	Overskilled	39.08	**27.59**	33.33
	Underskilled	41.48	34.09	**24.43**
		Part 2: Educational mismatch status		
		Year *t*		
		Well-matched	Overeducated	Undereducated
Year *t*-1	Well-matched	**41.03**	24.36	34.62
	Overeducated	30.00	**32.00**	38.00
	Undereducated	38.86	18.29	**42.86**

There are two potential explanations for these differential persistence rates between skill and educational mismatches. First, there might be more upward and downward rigidities[18] in mismatch status based on education than skills given that educational attainments and educational job requirements hardly change over a short period of time (2 years in the present study). In that context, over- or undereducated youth can only change their mismatch status by changing the job (Rubb, 2003; Frei and Sousa-Poza, 2012), which is particularly challenging in African countries where youth unemployment rate is often high and job mobility up the occupation ladder is low. In contrast, skill-mismatched youth can benefit from different training, financed by their employers or not, to bridge their skill deficits without necessarily being obliged to changing their job. This argument is supported by our data: in 49.3% of the cases, skills improvement was the main focus of the training received by employed youth. Second, the observed differences in persistence of job mismatch might be the result of unobserved heterogeneity between skill and education-mismatched workers such as personality traits, ability, motivation and other unmeasured skills we do not control for and

[18] Upward rigidity refers here to the transition from undereducation to job match and downward rigidity from overeducation to job match.

which could affect differently state dependence of skill and educational mismatches (Bauer, 2002; Chevalier, 2003; Blázquez and Burdía, 2012).

5.2. Skill and educational mismatches and the duration of unemployment spells

An obvious question that has arisen from the previous analyses is why, despite all the potential negative effects of job mismatch (wages penalties, lower productivity, lower job satisfaction, psychological stress, etc.), youth would continue to accept jobs for which they are mismatched in terms of either skills or education. In this section, we test two potential explanations often advanced in the literature: African youth accept a mismatched job as a desperate measure rather than waiting longer in unemployment (the so-called *scarring effect* of unemployment) (Arulampalam, 2001; Meroni and Vera-Toscano, 2017) or as a strategy to gain experience and eventually increase their chances of getting better-matched jobs in the near future (the so-called *stepping-stone hypothesis*) (Sicherman and Galor, 1990).

For first insights on the question, Table 5.2 reports the distribution of employed youth by job mismatch status for different durations of unemployment before accepting current job. It shows that the proportion of youth who accept a job that underutilizes their skills (i.e., they feel overskilled) or for which they are overeducated increases as they remain longer in unemployment up til about 6 months, before decreasing. In contrast, underskilled and undereducated youth behave differently: their proportion raises as their unemployment duration continues to increase. This preliminary result tends to confirm the scarring effect for underskilled and undereducated but a mix of both scarring effect and stepping-stone hypothesis for overskilled and overeducated youth, depending on the duration of their spell out of unemployment.

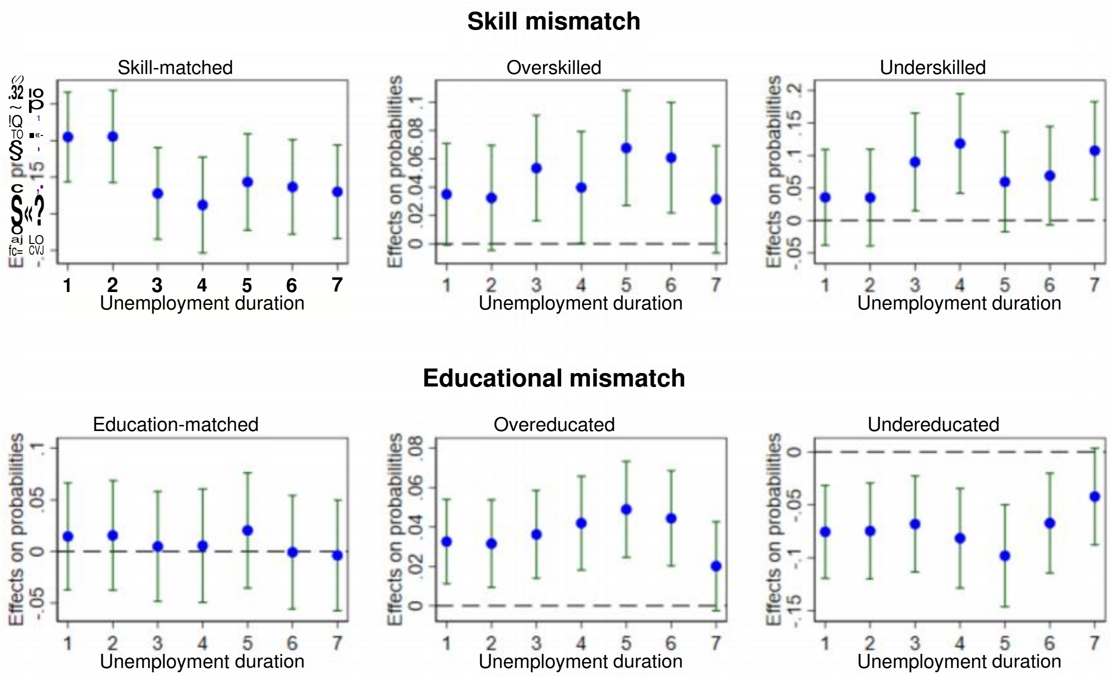
Table 5.2: Distribution of employed youth by job mismatch status and duration of unemployment

			Duration of unemployment before accepting current job ([a])						
			[0;1w[	[1w;1m[	[1m;3m[	[3m;6m[	[6m;1y[	[1y;2y]	>2y
Job match status	Skill mismatch	Well-matched	55.32	56.75	51.86	51.65	54	53.85	50.94
		Overskilled	17.34	19.35	20.39	17.69	20.62	19.81	16.24
		Underskilled	27.34	23.9	27.76	30.66	25.38	26.33	32.81
		Observations	9,037	3,489	3,311	1,696	1,513	2,024	3,078
	Educational mismatch	Well-matched	34.22	39.01	35.92	36.28	37.56	34.14	31.29
		Overeducated	7.33	8.76	9.38	11.74	11.23	9.95	7.97
		Undereducated	58.45	52.23	54.70	51.98	51.21	55.91	60.74
		Observations	7,846	3,140	3,082	1,593	1,443	1,869	2,672

Note: ([a]) The letters *w, m* and *y* refer to *w*eek, *m*onth, and *y*ear, respectively.

However, to go beyond these descriptive analyses and account for other factors that might explain the observed job mismatch status over various unemployment spells (such as personal and job characteristics), we estimate different probit models for each of the different mismatch outcomes and control for sample selection bias. We used the same set of variables as in our multinomial logit and selection models. Our key variable of interest is a categorical variable for the duration of unemployment before current job, taking the value 1 if the youth gets the job after less than a week of unemployment; 2 if unemployment duration was between 1 week and 1 month; 3 if it was between 1 and 3 months; 4 if between 3 and 6 months; 5 if between 6 months and 1 year; 6 if between 1 and 2 years; and 7 if the youth spent more than 2 years in unemployment before current job. Results from probit models corrected for sample selection bias are plotted in Figure 5.1 as average marginal effects on probabilities of being mismatched in the labor markets and in Table A.1 as coefficients of the probit models.

Figure 5.1: Average marginal effects of duration of unemployment on job mismatch status (Estimates from Probit models corrected for sample selection bias)



Note The figures report the estimated marginal effects of the duration of unemployment on the probability of having a match job or being mismatched in the labor markets Marginal effects are computed using the coefficients estimated using probit models corrected for sample selection bias The x-axis refers to the duration of unemployment before current job, ranging from 1 (*Less than a week), 2* (*Between 1 week and 1 Month),3* (*Between 1 and 3 months),* 4 (*Behveen 3 and 6 months),* 5 (*Between 6 months and 1 year),* 6 (*Behveen 1 and 2 years)* to 7 (*More than 2 years).*
Source: Autnors' computation based on ILO's STWT data, various countries and years

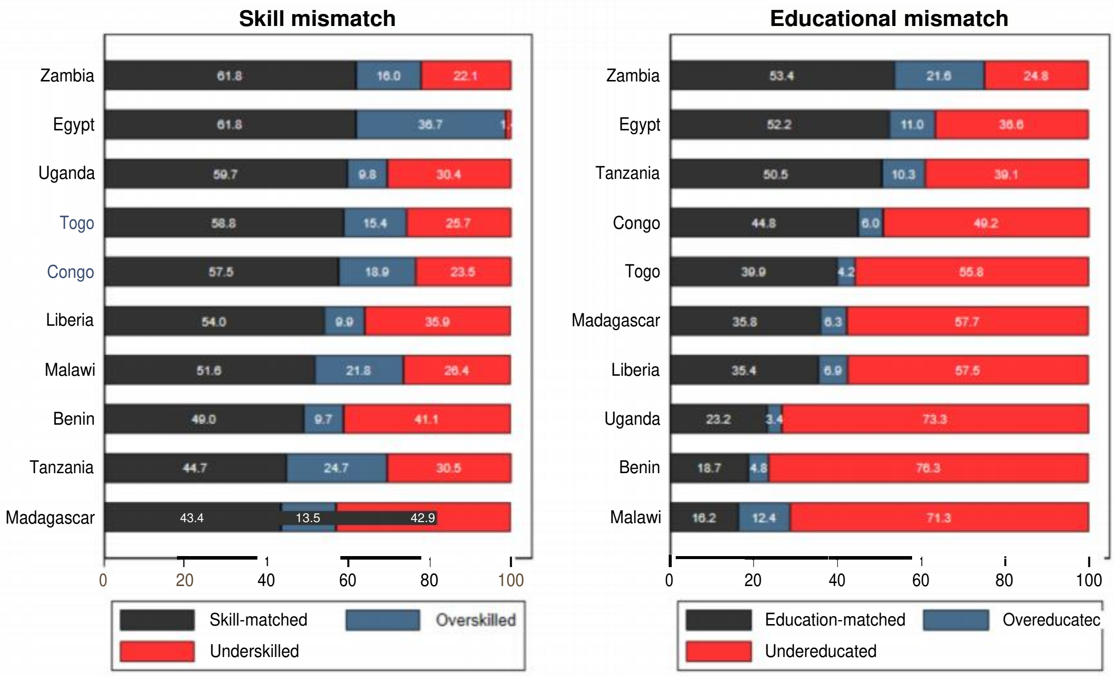
Focusing on mismatched workers, the graphs show for instance that the average marginal effect of accepting a job for which the youth is overskilled after less than a week in unemployment rather than waiting longer is 0.03. This means that, after controlling for other characteristics, there is 3% more chance that youth who accepted a job after being unemployed for less than 1 week will be overskilled than for those who got a job after spending longer periods unemployed. For overeducated workers, the average marginal effects of getting a job in which they are overeducated increase as the duration in unemployment increases but decline after being unemployed between 6 months and 1 year, confirming our preliminary results. For these two categories of young workers, the fear of remaining unemployed initially pushes them to accept the job for which they are either overskilled or overeducated but, as they gain experience, they feel more comfortable looking for better matched jobs. In contrast, the average marginal effects of underskilled are by and large increasing as their unemployment experience persists, confirming the scarring effect hypothesis. A particularly interesting result concerns skill-matched youth who present negative average marginal effects. This means that the predicted probability of getting a skill-matched job diminishes as the youth are unemployed longer, probably because employers might perceive, rightly or wrongly, that their unused skills may have tapered off the longer the duration of their unemployment (Arulampalam, 2001).

5.3. Accounting for countries and gender heterogeneities

Labor market opportunities for youth are likely to be affected by general labor market conditions and changes prevailing in the country they live in. For instance, in some countries, legislators may make it difficult, or even illegal, to discriminate against workers based on gender while in others they may offer better incentives to firms hiring youth. In some others, labor markets might be thinner, more rigid (particularly in smaller economies) and labor mobility across regions low, which reduces job opportunities for newly graduated youth entering the labor markets and increases their likelihood of ending up in mismatched jobs. The existence in some countries of better social protection mechanisms and benefits such as unemployment insurance or pension schemes might also affect differently the behavior of both unemployed and employed youth. Finally, greater integration of some countries with the international economy might increase their vulnerabilities to global shocks and amplify their impact on domestic labor markets.

To account for potential heterogeneity across countries and discrimination by gender, we replicate the analysis from the previous sections for each of the 10 selected African countries and estimate, separately by country and gender, the probabilities of youth being well or mismatched in their respective labor markets. Figure 5.2 presents the estimated predicted probabilities by country and Figure 5 provides gender differences in the predicted probabilities of job mismatch using multinomial logit models. After controlling for personal and job characteristics, the predicted likelihood of being mismatched perfectly mirrors the descriptive analyses reported in Figure 2.1.

Figure 5.2: Predicted probabilities of job mismatch by country



Note Predicted probabilities are derived from multinomial logit models estimated separately for each country-gender pair using the same set of covariates.
Source Authors' computation based on ILO's STWT data, various countries and years

Unsurprisingly, youth in larger economies (in terms of GDP)[19], have a better chance of displaying the appropriate skills for their job. In Zambia and Egypt, for instance, employed youth have a 61.8% chance of being skill matched in their job compared with 44.7% in Tanzania and 43.4% in Madagascar. In addition, Egypt, the largest economy in the sample with the one of the best education systems in Africa[20], has both the highest predicted probability of overskilled youth (36.7%) and the lowest probability of underskilled youth (1.4%). In contrast, the highest likelihood of underskilling is found in Madagascar (42.9%) and Benin (41.1%). In

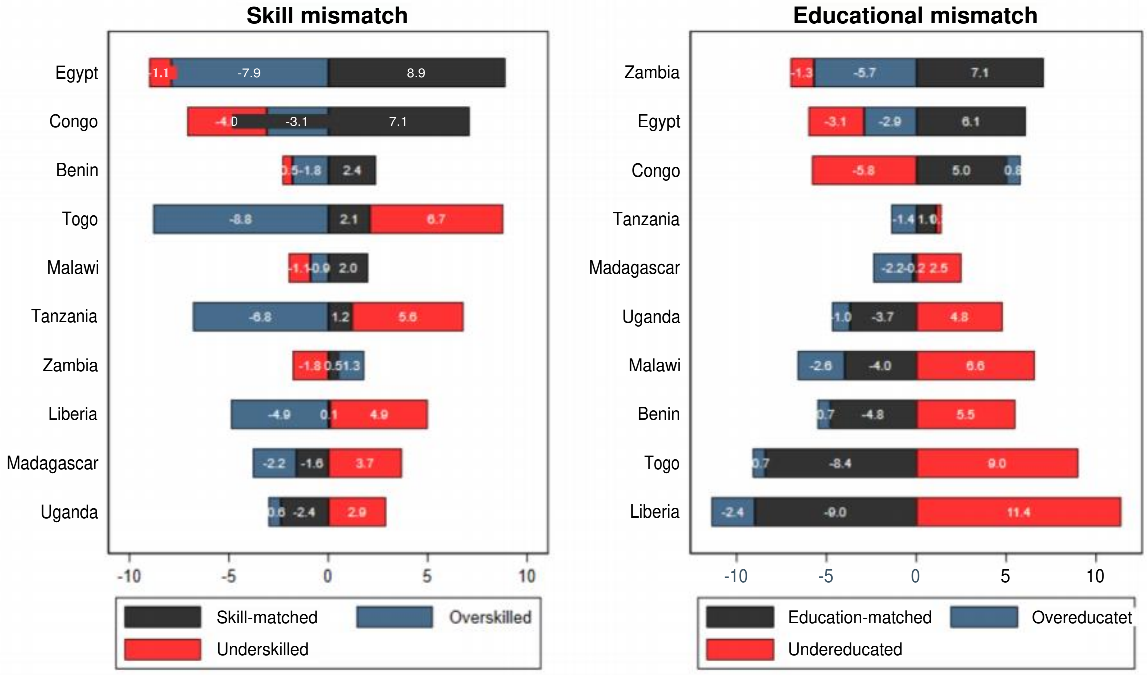
[19] During the time of the surveys (2012–2015), the average GDP (in constant 2010 USD) was USD 237.5 billion in Egypt; USD 39.8 billion in Tanzania; USD 24.6 billion in Zambia; USD 24.5 billion in Uganda; USD 13.8 billion in Congo; USD 9.3 billion in Madagascar; USD 8.2 billion in Benin; USD 8 billion in Malawi; USD 4.2 billion in Togo; and USD 2.5 billion in Liberia (World Bank, 2019).
[20] Egyptian universities are routinely classified among the best in Africa (see for instance the Shanghai ranking here: http://www.shanghairanking.com/ARWU2019.html

terms of educational mismatch, Zambia (53.4%) and Egypt (52.2%) present the highest chances of having youth with the required education as well as the lowest risk of having undereducated employed youth (24.8 and 36.6%, respectively). Tanzania, which was among the worst performers in terms of predicted skill mismatch, now outperforms the remaining countries, with a 50.5% chance of having well- matched youth. On the other hand, Malawian employed youth are the least likely to be well-matched and most likely to be undereducated, all else being equal.

One's gender significantly affects the likelihood of having a job match in the selected countries, in contradiction with the human capital theory which postulates that only the supplied human capital of youth should matter in the labor markets. Figure 5.3 shows that there are important gender differences in the probability of being matched or not, the magnitude of the gap varying from one country to another and depending on the type of job mismatch considered. Egypt, for example, presents the largest gender gap among well-matched youth: after controlling for personal and job characteristics, an employed Egyptian male is 8.9% more likely to be skill-matched than a female, and 6.1% more likely to have the required education level. In contrast, female Egyptians are 7.9% and 2.9% more likely to be overskilled or overeducated, everything else held constant. In the majority of the surveyed countries, the predicted probabilities of being overskilled and overeducated are higher for females than males, with Zambia and Tanzania being relatively more gender-neutral when it comes to skill and educational mismatches, respectively.

There are two potential explanations of the higher predicted probabilities of overskilling and overeducation among employed females. First, female labor market participation rates are lower than males' in most African countries as women face discrimination in accessing the labor market due to cultural, religious, and institutional factors. In Egypt, for instance, less than 20% of female youth aged 15–24 years old participated in the labor market during the survey period (2012–2015) compared with 48% for male youth. This means that women often have to work harder than males to increase their chances of finding a job and might then be more likely to accept jobs for which they are clearly overskilled or overeducated instead of remaining unemployed. Second, in line with Frank's (1978) theory of differential overqualification, women may prioritize their male partners' career success and job match instead of their own due either to men's higher probability of better earnings or to their motherhood roles, leading them to willingly accept mismatched jobs. In addition, in most African countries, women generally follow their husbands or partners when they are relocated by their employers to other cities or regions. As Mincer (1978) put it perfectly, female partners then behave like "tied movers" with employment outlooks that are probably better at their previous location, which increases the likelihood of ending up in overskilled or overeducated jobs.

Figure 5.3: Gender differences in predicted probabilities of being job mismatched by country



Note: Predicted probabilities are derived from multinomial logit models estimated separately for each country-gender pair using the same set of covariates. Positive values mean that employed male youth are more likely to be well-matched or mismatched in the labor market.
Source: Authors' computation based on ILO's STWT data, various countries and years

5.4. Approximating economy-wide costs of job mismatch in Africa

Estimation results from the previous sections suggest that job mismatch among African employed youth is not only persistent over time but also might have important efficiency implications by distorting the optimal allocation of resources and skills among the youth (Mavromaras et al., 2007). It is possible to make a rough estimation of the approximate overall costs to an economy of persistent skill and educational mismatches in Africa using results of wage penalties associated with labor market mismatches (overskilling, overeducation and underskilling)[21]. One way to do so is to combine the estimated wage penalties associated with job mismatch with the sample information on the number N of mismatched workers in each

[21] Given that being undereducated leads to a wage premium (see results from the Verdugo and Verdugo model), we only focus here on job mismatches leading with a wage penalty (Mavromaras et al., 2009).

country c. However, given that the distributions of skill and education mismatched workers overlap[22], we reestimate the wage equation (9) separately for skill and educational mismatches.

If productivity loss/gain of an employed youth due to job mismatch can be roughly approximated by the estimated coefficients from the wage equation, then the expected aggregate net value of productivity loss, $\widehat{W}_T$, conditional on being job-mismatched ($j \neq 3$) and expressed in terms of wages of matched workers is given by:

$$\frac{E\left(\widehat{W}_T|j \neq 3\right)}{\left(\overline{\mathrm{W}}_m^k N_m^k\right)} = \sum \hat{\beta}_o^k \left(\frac{\overline{\mathrm{W}}_\mathrm{o}^k}{\overline{\mathrm{W}}_m^k} * \frac{N_\mathrm{o}^k}{N_m^k}\right) + \hat{\beta}_u^k \left(\frac{\overline{\mathrm{W}}_u^s}{\overline{\mathrm{W}}_m^k} * \frac{N_u^s}{N_m^k}\right), \qquad k = \{skill, education\} \tag{12}$$

where the subscripts *o* and *u* refer to *over*skilling/*over*education and *under*skilling, respectively, depending on whether the skill mismatch (*k=skill*) or educational mismatch (*k=education*) model is considered. $\hat{\beta}$ are the estimated coefficients from the wage effect models; $\overline{\mathrm{W}}_m^k$, $\overline{\mathrm{W}}_\mathrm{o}^k$, and $\overline{\mathrm{W}}_u^k$ represent the average hourly wage received by *m*atched, *o*verskilled/*o*vereducated and *u*nderskilled subgroups of employed youth and N_m^k, N_o^k, and N_u^k, their respective sample size, with $N = N_m^k + N_\mathrm{o}^k + N_u^k$. The first (second) term on the right-hand side of equation (15) represents the approximate hourly aggregate cost of overskilling and overeducation (underskilling) as a percentage of hourly earnings of well-matched workers. The results of the computation are reported in Table 5.3 using the extended Verdugo and Verdugo model specification for the pooled sample controlling for country effects[23].

Estimation results show that the approximate hourly cost of overskilling is about 3.9% of hourly wages of skill-matched youth which, expressed in monetary terms, represents a monthly cost between USD 911,000 and USD 2.9 million for the whole sample[24], or an average monthly cost of USD 1.9 million. Applying a similar estimation procedure, Mavromaras et al. (2009), found for instance that the overall cost of overskilling in Australia represents about 2.6% of the country's GDP. On the other hand, overeducation costs to the surveyed countries come to 3.2% of the wages of better-educated youth or a monthly average cost of USD 778,000. Putting together all the estimated costs associated with job mismatch, the overall cost is roughly equal to 9.3% of hourly earnings of well-matched workers or around USD 3.7 million per month. However, as explained by Haskel and Martin (1996) and Dearden et al. (2006), the magnitude of these economy-wide costs of job mismatch estimated using wage penalties may

[22] See Figure 2.
[23] We omit the results at the country level because many coefficients of job mismatch variables were not statistically significant.
[24] Under the assumption that employed youth worked 8 hours per day, 6 days per week, for 30 days a month.

be underestimating the true penalties associated with job mismatch given that we are not controlling for key factors affecting firm productivity (inputs such as capital and raw materials, or union and firm market power)[25]. Our estimations should then be interpreted as an approximate lower bound of the aggregate effects of job mismatch in the selected African countries.

Table 5.3: Approximated productivity gain/loss due to job mismatches in Africa

	Skill mismatch			**Educational mismatch**	**Overall cost**
	Over-skilling	Under-skilling	Total	Overeducation	
$\hat{\alpha}^k$	-0.171	-0.052	-	-0.152	
	[-0.260; -0.083]	[-0.165; 0.060]		[-0.264; -0.040]	
	(0.044)***	(0.057)		(0.056)***	
$\frac{\bar{W}^k}{\bar{W}^k_m}$	0.702	0.774		0.904	
$\frac{N^k}{N^k_m}$	0.327	0.538		0.238	
$\frac{E(\widehat{W}_c \mid j \neq \text{:}}{(\bar{W}^k_m N^k_m)}$	-0.039	-0.022	-0.061	-0.032	**-0.093**
	[-0.060; -0.019]	[-0.069;0.025]	[-0.128;0.006]	[-0.057; -0.008]	**[-0.185; -0.002]**

Note: The estimated coefficients $\hat{\alpha}^k$ are derived from the IV-2SLS method corrected for sample selection bias on the pooled sample of employed youth (see section 3.2.1). [] stands for the 95% confidence interval. (***) refers to significance at 1% level. Bootstrapped standard errors (with 10,000 replications) into brackets. Source: Authors' computations.

6. Conclusion and policy implications

This paper examined the incidence and the effects of skill and educational mismatches among employed youth (aged 15–29) in 10 African countries, namely Benin, Congo, Egypt, Liberia, Madagascar, Malawi, Tanzania, Togo, Uganda, and Zambia surveyed between 2012 and 2015. In particular, the paper investigated whether, after controlling for personal and job characteristics, skill and educational mismatches have significant effects on youth's wages, their job satisfaction and their likelihood of job search. In addition, the paper shed light on the persistence of job mismatch over time and the existence of country and gender heterogeneities

[25] The surveys did not collect data on physical output and inputs of the firms employing the youth.

in the risk of being job mismatched, as well as the approximate economy-wide costs of skill and educational mismatches in Africa.

Our findings revealed that over 17.5% of employed youth felt overskilled in their current job and 28.9% experienced important skill deficits when performing their work-related duties. Overskilling was more pervasive in Egypt (36.6%) and Tanzania (24.3%) whereas underskilling was is important in Madagascar (42.5%) and Benin (41.0%). In contrast to findings in developed countries, our results showed that a larger share of employed youth in African countries worked in jobs for which they were undereducated (56.9%) than overeducated (8.3%), with significant cross-country differences. Moreover, our results established that, contrary to the assumption of the assignment theory, educational mismatch is neither a necessary nor a sufficient condition for skill mismatch because a non-negligible share of over- and undereducated youth perceived their skills as being appropriate to perform their current job.

A number of methods were used to estimate the wage effects of skill and educational mismatches in Africa. Applying an IV-2SLS method accounting for sample selection bias, results from the Heckman-corrected Mincerian earning equations strongly rejected the hypotheses from the human capital and job competition theories that job mismatch is not irrelevant for wage determination of employed youth. In particular, the average wage penalty associated with overskilling and overeducation was estimated at 6.7% and 17.9%, respectively, whereas undereducation was associated with a wage premium of 44.8% using an extended Verdugo and Verdugo model.

Our results from the IV ordered Probit model corrected for sample selection bias supported the predictions from the relative deprivation theory as skill and educational mismatches were found to damage youth's perceptions of their job satisfaction. Overskilled and underskilled youth have respectively 3.4% and 1.8% less chance of feeling satisfied in their current work compared with youth possessing the appropriate skills, consistent with empirical evidence (Green and Zhu; 2008; Amador et al., 2012; Allen and van der Velden, 2001; McGuinness and Sloane, 2011; Sánchez-Sánchez and McGuinness, 2015). Overskilled youth are probably less satisfied with their jobs as they might foresee little career opportunities, feel that their skills are not optimally leveraged or might fear that their unused skills could depreciate over time. On the other hand, the pressure and the need to regularly keep up with the skill requirements of a job and the constant fear of losing a job due to skill insufficiency might affect the perceived satisfaction of underskilled youth.

The paper also highlighted the behavioral consequences of skill and educational mismatches of employed youth as the findings suggested that mismatched youth were more likely to search for alternative jobs to replace their current job than their peers who are better matched. One additional year of overeducation was estimated to have increased by 0.18% the likelihood of seeking alternative jobs while overskilled youth were 0.31% more likely to apply for other jobs to replace their current job. By contrast, undereducated youth were found to be less likely to search for alternative jobs either because they might feel they were lucky to be employed in spite of their educational deficits or because they might offset their formal educational handicap with specialized vocational and on-the-job training.

Using a pseudo-panel approach, we also tested the predictions of the job search and job matching theories that job mismatch among African youth is a transitory phenomenon. Our estimated transition probability matrices indicated that job mismatch is rather persistent for employed youth as skill- and education-matched youth cohorts had, respectively, only a 34.9% and 41% chance of remaining well matched after 2 years. Mismatch state dependence was found to be more severe for educational than skill mismatch, as evidenced by the 4.4 percentage point gap between the probabilities of staying overeducated and overskilled during the survey period. Finally, being skill mismatched was found to offer more chances to transition toward better job match than lacking the required education level. Specifically, youth cohorts who were either over- or underskilled in the initial surveys had, respectively, 39.1% and 41.5% chance of feeling well-matched in the follow-up surveys, against 30% for overeducated and 38.9% for undereducated, respectively. The paper discussed potential explanations of these differential persistence rates between skill- and education-mismatched youth cohorts in terms of rigidities to changes in educational attainments and educational job requirements but also the existence of potential unaccounted for and unobserved heterogeneity (related to personality traits, ability or motivation).

Further insights were also given on the scarring effect and stepping-stone hypothesis as potential explanations of why African youth might accept jobs for which they are mismatched, with different results depending on the type of job mismatch analyzed. For instance, our findings confirmed the scarring effect hypothesis of underskilled youth, implying that they had probably accepted a mismatched job as a desperate measure instead of waiting longer in unemployment for a better job match. Overeducated and overskilled youth were found to display a dual behavior: for shorter spells of unemployment (between 6 months and 1 year), they were willing to accept a job for which they were overskilled or overeducated instead of remaining unemployed (scarring effect hypothesis). However, beyond that period, they started looking for better matched jobs as they had gained experience, the mismatched job having only served as a springboard (stepping stone hypothesis).

The findings of this paper have important policy implications given the magnitude of skill and educational mismatches, its adverse effects at both the individual level (wage penalty, low job satisfaction and labor productivity) and aggregate level, and its persistence over time. First, African countries must develop policies that clearly facilitate school-to-work transition of their youth. The surveys revealed indeed that the overwhelming majority (around 97%) of youth (employed or not) did not receive any kind of advice from job search agencies or the government to find a job. The most common obstacles to finding a job that they faced were high educational criteria, lack of professional experience, unavailability of jobs and lack of knowledge on how to look for a job. Governments need therefore to implement structures that facilitate easy access to information on job availability as well as provide incentives (such as tax reduction or subsidy schemes) to encourage firms to offer internships and apprenticeships to youth graduates. In countries where these structures already exist, their efficiency and efficacy should be improved, their mandates better defined, their existence better advertised and their performance better monitored.

Second, despite significant strides being made by many African countries to improve access to education, there is still ample room for improvement as too many youth, especially females and those living in rural areas, have yet to benefit from better national education systems. The surveys showed that 38% and 11.5% of employed youth never attended school for economic reasons or because there was no school nearby, thereby missing the opportunity to improve their human capital. Investment in soft and hard infrastructure (construction of new schools, renovation of old ones, modern school equipment, better teachers' working conditions, ICT infrastructure, etc.) will therefore be crucial to increase the chances of these youth getting better-matched jobs. Abolition of school fees to accelerate universal access to primary education, better control of education costs at secondary and tertiary education levels, and the generalization of scholarships would have a positive impact on education outcomes.

Finally, countries should aim at diversifying the range of skills/education available for the youth as one of the recurrent complaints from employers is the impossibility of finding very specialized skills on the continent for sectors such as robotics, information and computer technology (ICT), automation, (advanced) engineering, etc. In particular, STEM (science, technology, engineering and math) skills as well as social, system, complex problem-solving and critical thinking skills are often lacking among recent graduates; only 6.1% of surveyed youth followed STEM curricula. Countries can achieve this objective by making their education systems more demand-driven to address the observed persistent mismatch in the labor markets. This will also increase the relevance and attractiveness of education for the youth as 38.2% of surveyed youth considered that their education was not useful in finding jobs. Countries can for instance institutionalize forums where education/training institutions and firms can “speak to each other” and establish sectoral skill strategies that identify the range of skills needed by different economic sectors. In that way, education institutions can adapt their curricula to the requirements and needs of the labor markets and firms can be sure to fill their vacancies with skilled workers without having to import them from overseas. A forward-looking approach should however guide this process, to account for the constant changing dynamics of the labor markets, and anticipate the skills needed for the future.

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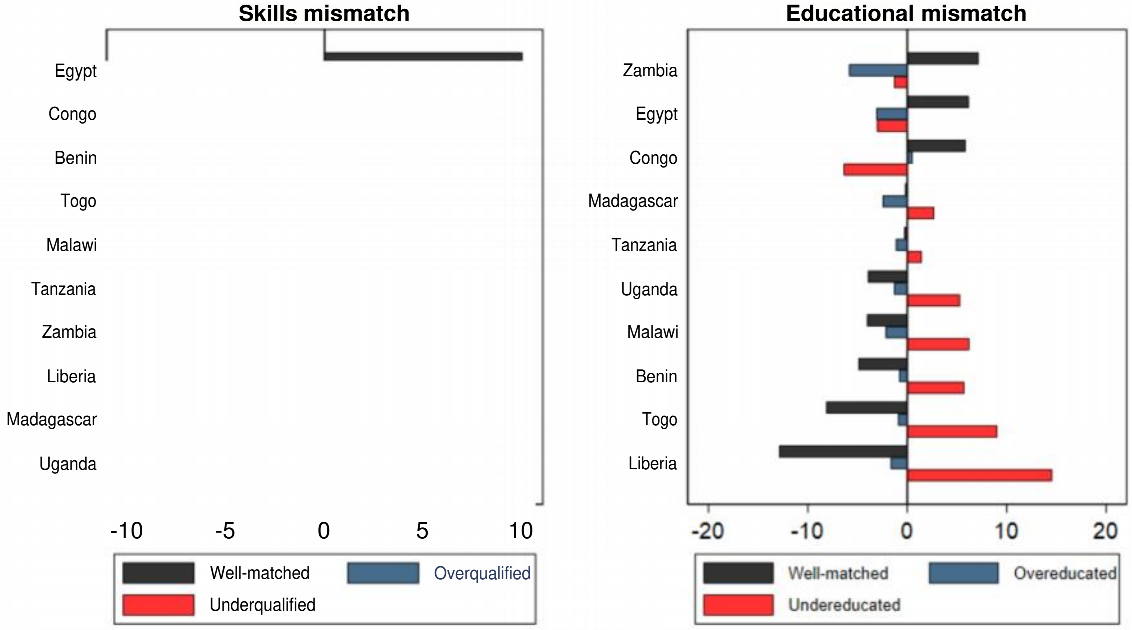
Appendices

Figure A.1. Gender gaps in the incidence of skill and educational mismatches in selected African countries

Average % of employed youth per country, 2012-2015



Note: Gender gaps refer to the difference between the shares of employed males and females by mismatch group in each country. Positive values imply that the share of employed males is higher than females' for the mismatch group considered.
Source: Authors' computation based on ILO's STWT data, various countries and years

Table A.1: Probability of being job matched given the duration of unemployment before current job (Probit model corrected for sample selection bias)

	Duration of unemployment	Coeff. (std. err.)
1. Being skill-matched	[0;1w[	-0.268 (0.092)***
	[1w;1m[	-0.266 (0.094)***
	[1m;3m[	-0.473 (0.094)***
	[3m;6m[	-0.515 (0.097)***
	[6m;1y[	-0.432 (0.098)***
	[1y;2y]	-0.450 (0.096)***
	>2y	-0.467 (0.095)***
2. Being overskilled	[0;1w[	0.171 (0.097)*
	[1w;1m[	0.160 (0.099)
	[1m;3m[	0.252 (0.099)**
	[3m;6m[	0.193 (0.104)*
	[6m;1y[	0.311 (0.104)***
	[1y;2y]	0.283 (0.102)***
	>2y	0.155 (0.101)
3. Being underskilled	[0;1w[	0.135 (0.148)
	[1w;1m[	0.133 (0.149)
	[1m;3m[	0.326 (0.150)**
	[3m;6m[	0.420 (0.152)***
	[6m;1y[	0.220 (0.153)
	[1y;2y]	0.253 (0.151)*
	>2y	0.384 (0.150)**
4. Being education-matched	[0;1w[	0.049 (0.089)
	[1w;1m[	0.052 (0.092)
	[1m;3m[	0.016 (0.092)
	[3m;6m[	0.018 (0.095)
	[6m;1y[	0.068 (0.096)
	[1y;2y]	-0.002 (0.095)
	>2y	-0.013 (0.093)
5. Being overeducated	[0;1w[	0.424 (0.172)**
	[1w;1m[	0.413 (0.175)**
	[1m;3m[	0.463 (0.175)***
	[3m;6m[	0.522 (0.180)***
	[6m;1y[	0.590 (0.181)***
	[1y;2y]	0.546 (0.181)***
	>2y	0.280 (0.179)
6. Being undereducated	[0;1w[	-0.299 (0.091)***
	[1w;1m[	-0.295 (0.093)***
	[1m;3m[	-0.270 (0.094)***
	[3m;6m[	-0.322 (0.097)***
	[6m;1y[	-0.386 (0.099)***
	[1y;2y]	-0.267 (0.097)***
	>2y	-0.169 (0.094)*

Note: [0;1w[: Less than a week of unemployment before getting current job; [1w;1m[: unemployment duration between 1 week and 1 month; [1m;3m[: Between 1 and 3 months; [3m;6m[: Between 3 and 6 months; [6m;1y[: Between 6 months and 1 year; [1y;2y]: Between 1 and 2 years; >2y: More than 2 years in unemployment before current job. Robust standard errors in brackets. (*), (**), and (***) refer to statistically significant coefficients at least at 10%, 5% and 1% level, respectively.