Informal vs formal skills and earnings for low educated: Evidence from Senegal

Racky Balde, UNU-MERIT, Maastricht University

email balde@merit.unu.edu

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Abstract

In Senegal, most of the low educated people acquire skills in the informal sector. There is a debate about the recognition of these skills in order to lead to better outcomes for those people. In this paper, we use the representative Survey of Monitoring Poverty in Senegal conducted in 2011 to ask whether it makes any difference on earnings whether you have informal or formal skills when you are low educated. We find that for wage earners both informal and formal skills have almost similar and significant impact on earnings when you are low educated. Whereas, for self-employed, none of them has a significant effect. A further investigation for self-employed in non-agricultural activities with a finite mixture model shows that informal skills have an effect only on one segment and that segment might be those who are running a business survival without growth potential. At some point, self-employed with growth potential need more elaborated skills acquired through the formal system. Our results are consistent with low education being a trap, and either having formal or informal skills does not make any difference for low educated wage earners.

Key words: Informal sector; Skills; Education
JEL Classification:O17;J24

1 Introduction

In Sub-Saharan Africa, more than 70% of people are in vulnerable employment. While this region has a growing youth population. Youth unemployment is an impediment to the development of the region. In Senegal, the unemployment rate is around 13.4% according to the last survey conducted in 2015. The majority of unemployed is youth aged 15 to 34. The population is weakly educated with a literacy rate around 44.8%. The low level of education makes hard to get a job, particularly a decent job in the formal sector. Despite increasing education expenditures, 66% of youth don't complete the primary level and they end up without skills. According to the World Bank, as one goes along in different education level the number of youth excluded from general education increases. Still, with the World Bank document, these youth are often unemployed or underemployed due to their weak productivity. They are therefore, exposed to job insecurity and poverty. Indeed, in Senegal the job earnings represent about 80% of income. In Sub-Saharan region, informal economy provides 60-80% of the employment.

According to Eichhorst et al., (2014), in developing countries, the majority of low educated people acquire skills in the informal sector. This result is understandable insofar. It is easier to access to skills in the informal sector than in the formal educational system. There are no fees or fewer compare to the formal educational system. This fact is confirmed by Rodriguez et al. (2014), who state that due to high fees and poverty the enrolment rate into secondary school is far to be high. The informal sector is more attractive somehow it is a shorter way to enter the labor market. Many apprentices end up as employees of their masters. The informal sector is now widespread in developing countries. It is then important to address the question related to the effects of informal skills for low educated people. Do informal skills improve their earnings? How are the effects compared to the effects of formal vocational school?

Facing unemployment issues, many policies have been initiated by the government of Senegal. Particularly the Decennial Plan for Education and Vocational Education (PDEF). These policies aim to improve the skills, focusing on those who are vulnerable in the labor market and the main way is the vocational education. Indeed, skills development had been often the main way to overcome unemployment in several countries in the world. According to Ashenfelter (1978), in the United States, one of the main reasons for training programs is the reduction of unemployment and poverty of youth by giving them competencies. Attanasio et al., (2011), think that training program may offset the lack of competencies for those who did not complete general education or did not enroll in school. In developing countries, the main way to get skills for low educated people is in the informal sector.

According to Eichhorst and al., (2014) in India and many African countries, the predominant source of training occurs in a so-called traditional or informal apprenticeship system, which lies outside of the formal vocational or general schooling. As Rodriguez-Planas and al. (2014) said, given the cost of school attendance and weak family background in some countries, enrollment in secondary education is low. Consequently, some young people are seeking an apprenticeship in a small business. NGOs, churches, and informal entrepreneurs deliver major parts of VET in Africa (Rioust de Largentaye, 2009). We have to be clear about the types of skills we are referring to. By informal skills we mean skills acquired in traditional or informal apprenticeship system or out of the educational system and by formal vocational education we mean skills acquired in the formal educational system. Card and al.(2011), find in Dominican Republic that the effects of job training increase wage. Many studies have showed that informal skills have positive and significant effects on earnings (Monk and Steal, 2008; Grootaert, 1990). According to Cano-Urbina (2015), low educated people in the informal sector experience faster growth wage than their peer in the formal sector. Albeit, the informal sector is now well known for giving skills to low educated people, the recognition of these skills is yet not well addressed. According to Palmer (2008), the recognition of these skills may benefit to people who have acquired informal skills. Indeed, having formal skills may lead to better outcomes because it is a signal of ability. In Senegal some reforms have been implemented to recognize the skills acquired in the informal sector (Rioust de Largentaye, 2009). But in the literature, there is no answer to the question when you are low educated, does it make any difference to have formal or informal skills. Due to the fact that low educated people have lower chances to get better jobs, informal skills might be more rewarded because they are more practical than formal ones.

In this paper, we estimate the returns of informal skills compared to formal vocational education for low educated people. We first estimate a Heckman selection model for both self-employed and wage earners to tackle both selection bias into the labor market. Secondly, an IV model is estimated to tackle both selection bias and endogeneity bias for different types of education (general education, informal skills, formal vocational education). For all instrumental variables, family background is used. The estimations are made for different samples of independents and wage earners. For each of them, we first estimate a full sample without making any difference between low educated and high educated and a low educated sample including only low educated workers.

The study has shown that after controlling the endogeneity bias related to the different kind of skills, whether you have formal or informal skills does not make any significant difference on earnings when you are low educated. For low educated wage earners, both formal and informal skills have a significant effect on earnings without significant differential impact. This might be explained by the fact that low educated people are mostly involved in low paid job. While in these kinds of jobs, practical knowledge is more rewarded. For self-employed, informal skills and formal skills are not significant at all for low educated people. One of the explanations could be the main sectors where self-employed are, such as agriculture and retail trade. In these activities, vocational education hasn't much importance. Indeed agricultural activities are not modern, they use often ancient tools and knowledge, and in retail trade, you don't need particular skills. They need more financial literacy in order to manage better their activities. But we need to be aware that the estimations are made on the mixed incomes from self-employment. A further investigation with a finite mixture regression of the effects of informal and formal skills for self-employed involved in non agricultural activities show interesting results. The segmentation of the self-employed between two segments shows that informal skills have an effect only on one segment and that segment might be those who are running a business survival without growth potential. Indeed, having access to credit is negatively correlated with the belonging to that particular segment. At some point self-employed with growth potential need more elaborated skills acquired through the formal system.

The next section will outline the literature on the relationship between skills (formal or informal) and labor market outcomes. In section 3 and 4 we present the data and the models used. In section 5, the main results will be presented and a final section will conclude.

2 Insights from the literature

Since Becker (1962) and Mincer (1974), it is clear that human capital accumulation may improve income. In the literature, Skills development for low educated relie often on vocational education and job training. In developed countries, the effects of job training on labour markets outcomes are mitigated. One of the early papers about job training (Ashenfelter, 1978) finds significant and positive effects of job training. In that paper, the author tries to evaluate the impact of job training program on youth labor market thanks to panel data. These youth have been randomly selected in order to attend training during three months. By regressing an earning equation, he found for men an increasing of income superior to \$150 juste after the end of the training. Women registered higher impacts, their income increased by \$300. Unlike (Ashenfelter, 1978) last studies on developed countries report insignificant impact. Bradley and al., (1999) find in the United States a lower impact of job training on labour market outcomes.

In developing countries, there is few evaluation of job training due to a seldom of data. The majority of these evaluations are in Latin American countries. In Peru, a program of job training has been evaluate by Pena(2011). By applying a propensity score method, he compares treated and no treated and take into account the completion or not of the training. The results showed that the effects on employment are significant only six months after the training and also the effects on earnings decrease with time. Others researchers had looked at the effects of training, mixed with classroom and practice in an enterprise like Card et al., (2007). By conducting the first randomized evaluation of job training in the Dominican Republic, they find that there is not a significant effect of job training on employment, and on the number of hours worked. But, the effect is significant on the earnings. They find also this effect increases with the education level. When researchers look at the effects of job training by gender in developing countries, they find usually more impacts for women. Indeed, Attanasio and al., (2011) by evaluating the impacts of the program "Youth in action" in Colombia find a wide and significant effect on employment salary, number of hours worked and wage for women. However, for men, there is not any impact on these different outcomes. These positive impacts of job training for women are corroborated by a meta-analysis from Betcherman et al., (2004). They use 159 papers about job training and find that women benefit more. In rural area, most of the research focus on the effect of job training on the diversification of income. Chun and Watanabe (2012) try to evaluate the effect of a job training program of three months in rural China. The skills acquired was about carpentry, masonry, plumbery and electricity.They find an improvement of diversification of income sources. Still, in China, Xie and al., (2012), find also, a positive impact of the Rural Labor Force Training Program on diversification of income sources and earnings. Generally, the main outcomes variables used in the evaluation of job training are employment, earnings and number of hours worked, but in Africa, self-employment is also taking into account. Bandiera and al., (2012) evaluate a program of formation and information of teenage girls. They find a high probability to become self-employed. Also, Yoonyoung (2013), by evaluating a job training program for youth aged between 15 to 34 years, find a positive effect on being self-employed.

Some studies focus particularly on the skills acquired in the informal sector. Monk and Steal (2008), find in Ghana that apprenticeship increases by over 40% the earnings of people without formal education. This effect is lower as the level of education increases. Blaak et al., (2013), found for youth aged 15 to 24 in Uganda significant impact of informal skills. Their results show that no formal vocational education can improve the empowerment for those being excluded from the formal system by giving them knowledge and skills. They argue that an adequate assessment and certification could contribute to an uplifting of the image and recognition of abilities of participants of non-formal education programs. Imoro and Nti (2009), show in Uganda that the use of master-craftsmen can improve the labor market outcomes for those who attend these vocational programs. Reis (2012) in Brazil find that vocational education improves the probability to work in the formal sector and increases earnings. These results are intensified for those who are low educated.

In terms of comparison between formal skills and informal ones, Grootaert (1990) in his study on Ghana, show that one year of informal or formal vocational education increases by over 10% the earnings. However, he did not make difference between low and highly educated people. Moreover, the study is limited to wage earners. Cano-Urbina (2015), shows that young low educated people in the informal sector experience faster wage growth than their peer in the formal sector.

It is still unclear, whether formal or informal skills lead to different significant outcomes when you are low educated.

3 Data

This study makes use of cross-sectional data, which are from the representative Survey of Monitoring Poverty in Senegal conducted in 2011. It is constructed by the National Agency of Statistics in Senegal. The sample data are gathered from individuals and households. This survey covers both rural and urban areas. The survey contains personal and labour market characteristics, including monthly wage, the type of vocational education, the highest level of education achieved, marital status, health conditions, the sector of activity and experience. We focus on individuals aged 5 years or more. This sample is chosen because in Senegal legal age of entry or retirement is just limited to the formal sector which represents only 9%. Child labor is a reality and all individuals who report an activity 7 days before the survey are included in the sample, also those who state that the reason for not working is due to vacation or strike. We make difference between wage earners and independents[1]. In the full sample, 10% have a vocational education. Among those with a vocational education 61% have an informal one and they are 86% with no education or just a primary level. The main fields of interest are agriculture (21.95%), joinery (5%), mechanics (5%), craft industry (3%), and trade (3%). By informal vocational education, we mean on the job training in an informal framework. It is in Senegal the main way for less educated to acquire skills in order to get a job (Nordman and Pasquier-Doumier, 2014; Chort et al.,2014). The dependent variable for this research is the natural log monthly earnings. The ESPS reports monthly earnings[2], and like Grootaert (1990) said for Ivory cost, the Government of Senegal publishes its payscale on a monthly basis, and frequently the private sector uses monthly terms in wage contracts. Hence, monthly earnings constitute the relevant transaction price for wage labor in Senegal, so we use monthly earnings as the dependent variable. Table 1 presents the summary statistics of variables used in the regression. We have the variable outcome (logearning) and variables related to both selection equation and earnings equation. The definition of all variables are summarized in Table 6 of the Appendix.

Table 1: Summary statistics

Variable	**Mean**	**Std. Dev.**	**N**
logearning	10.145	1.305	46915
Experience	11.713	11.833	46915
Worker	0.158	0.365	46912
Independent	0.407	0.491	46912
Other employment status	0.407	0.491	46912
Informal	0.905	0.293	46915
Primary	0.476	0.499	46915
Secondary	0.117	0.321	46915
Tertiary	0.304	0.46	46915
Other industry	0.103	0.304	46915
Private	0.948	0.221	46915
Married	0.43	0.495	122256
Single	0.505	0.5	122256
Other marital status	0.065	0.246	122256
sex	0.459	0.498	122256
Age	28.893	18.127	122256
Education	3.001	3.91	122256
disability	0.044	0.205	122256
rural	0.494	0.5	122256
none formal vocational education	0.062	0.241	122256
formal vocational education	0.039	0.194	122256
without vocational education	0.899	0.302	122256

[1] the sample named independents contains those who are self-employed or are employers

[2] the questionnaire asks the monthly earnings of your main activity

4 Methodology

The empirical results were obtained by regressing a version of the Mincer (1974) equation, under Beckers (1975) framework. A number of different approaches were employed in order to mitigate problems such as selection bias and endogeneity. We make difference between wage earners and independents. According to Grootaert (1990) and Bhatti (2012), the findings of the role of human capital for the earnings of the independents should be treated with precaution. The former assesses that complete analysis is needed which explicitly considers other input such as machinery and equipment raw materials, land and building and the use of family and hired labor. Some researchers such as Krueger and Summers (1988) have argued that extra determinants need to be included in the specification (quoted by Andersson and al.,2014, page 6). We so estimate this following equation:

$$lnY_i = \beta_0 + \beta_k X_i + \epsilon_i \tag{1}$$

X_K is the value of ith individual for kth explanatory variable, β_k are the coefficients associated to K explanatory variables respectively and ϵ_i is error term of the model assumed to follow normal distribution with zero mean and a constant variance. The Xs are the variables that are included in a design matrix like schooling[3], formal vocational education, informal vocational education, age, age squared, and variables related to the main activity like industry, socio-professional category, the private sector, labour market experience and other variables believed to affect the wage determination process in the relevant labour market at the individual level

4.1 Sample selection model

In order to correct the impact of sample selection bias on the estimated coefficients related to different wage determinants, we estimate a sample selection model. We use the Heckman (1979) two-step procedure to correct the possible bias due to non random selection of individuals into wage earners sample. According to Grootaert (1990), OLS estimator works if wage earners are a sub-sample of the whole population. The coefficients may be biased if it is not the case, so to deal with selection bias we apply a Heckman procedure (1979) to overcome that. For this purpose, we first estimated a participation or selection equation in which we regress binary response variable indicating the positive or negative outcome of whether an individual decides to participate in the labor market. Finally, we estimate the earnings function with the inverse of Mills ratio.

According to Wooldridge (2012), in sample selection model we do need to have at least a variable that affects selection but does not have a partial effect on the outcome. This is not absolutely necessary to apply the procedure, but the results are usually less than convincing unless we have an exclusion restriction. Indeed, the specification of the selection equation involves delicate identification issues. For example, if the nonlinearity implied by the probit model is slight, then the identification will be fragile (Cameron and Trivedi, 2009). We then use four exclusion restrictions in the structural equation. We so exclude married, single, other marital status, and disability from the wage equation. We choose these variables because we make the assumption that they can affect the decision to enter into the labor market. To be disabled can stop working and all marital status can influence the decision to participate in labor market. If we allow all variables in the selection equation to also appear in the wage offer equation, the estimates become very imprecise (Cameron and Trivedi, 2009). Firstly we estimate a selection equation by probit regression. The two-equation model comprises a selection equation for y_1

$$\begin{cases} y_1 &= 1 \; if \; y_1^* > 0 \\ y_1 &= 0 \; if \; y_1^* \leq 0 \end{cases}$$

[3] we use high level of education achieved with success

and a resultant outcome equation for y_2, where

$$\begin{cases} y_2 & = & y_2^* \ if \ y_1^* > 0 \\ y_2 & = & - \ if \ y_1^* \leq 0 \end{cases}$$

Here y_2 is observed only when $y_1^* > 0$, The classic version of the model is linear with additive errors. It is assumed that the correlated errors are jointly normally distributed and homoscedastic.

4.2 IV2SLS Estimation Approach

In order to address the endogeneity of certain variables related to education like educational level, formal or none formal vocational education we have to find instruments. The most common method used in the literature is the IV approach, which involves trying to find instruments that are exogenous and correlated to ability but not to income. Essentially, two different types of IVs are used in the literature, namely, institutional IVs and family background instruments (Andersson and al.,2014) For all instrumental variables, family background is used. Family backgrounds are usually used to address endogenous variables of education. Since in Africa, decisions about schooling, expenses and other are relevant to the household head, his level of education, his formal or no formal vocational education may influence these variables for all other members. So we propose two instrumental variables for each endogenous variable. For formal vocational education, we have the formal vocational education of household head and the number of individuals who attending formal vocational education. For none formal vocational education we have the none formal vocational education of household head and the number of individuals in household who attending none formal vocational education level of education and no formal vocational education. For educational level, we choose like instruments, the educational level of household head and the mean of household's educational level. We have then an overidentified model. We will also incorporate in the model estimated by iv approach, the inverse of mills ratio obtained after a probit regression (Wooldridge, 19.6.2). We will have this following equation.

$$lnW_i = \beta_0 + \beta_k X_i + imr + \epsilon_i \tag{2}$$

4.3 Finite mixture model for self-employed

Gunther and Andrey (2012) and Arati (2013) consider the informal sector to be segmented (heterogenous).This means that there is a number of latent segments in the labor market and each segment is characterized by its own unique earnings function. They, therefore, implement a finite mixture model to analyze the earnings in every segment. We will use the same reasoning for the self-employed. In the literature, self-employment is widely recognized as being heterogenous (Calza and Goedhuys, 2017; Gindling and Newhouse, 2014).Self-employment is seen as being composed of some of high potential growth and others as business survivals without any growth potential. We then, consider this heterogeneity and try to find out whether informal skills have an impact according to the segment you belong and what determine a self-employed to belong to one of these segments.

We follow the model specification of Gunther and Launov (2012) and Arati (2013). Self-employment is supposed to be heterogeneous, characterized by J segments with the earning determined by individual characteristics in each segment.

$$lnY_{ij} = \beta_0 + \beta X_{ij} + \epsilon_{ij} \quad \epsilon ij \sim N(0, \sigma_{ij}) \tag{3}$$

The errors terms of each segment are uncorrelated. when the sample selection is taken into account the probability $P(i \in Y_j) = \pi_j$ for any self-employed i that belongs to any segment Y_j

$$f(y_i) = \sum_{j=1}^{J} \pi_j f(y_i)|y_i^* > 0; \theta_j) \quad \theta_j = \{\beta_j, \sigma_j, \rho_j\} \tag{4}$$

In the previous equation, σ_j represents the self-selection into the labor market[4]. We add next to the model a set of concomitant variables Z, in order to analyze which variables determine to belong to one segment or another. We finally estimate the following equation.

$$f(y_i) = \sum_{j=1}^{J} \pi_j f(y_i)|y_i^* > 0; \theta_j) \quad \theta_j = \{\beta_j, \sigma_j, \alpha_j, \rho_j\} \tag{5}$$

With α_j the coefficients of the concomitant variables.

5 Results

We will first present estimates from the Heckman selection framework and estimates from the instrumental variables strategy. We will then, analyze the results from the finite mixture model for the self-employed to take into account their heterogeneity.

5.1 Impacts of informal and formal vocational education on earnings

In order to assess the impact of two kind of vocational education on earnings we conducted two types of estimation on both samples of wage workers and independents. For wage workers and independents we estimated first the whole sample and then the sample of those who are not or less educated. The two methods used are the Heckman two-step and the instrumental variable. In the first results, we tackle only the selection bias, in the second results, we tackle both selection bias and endogeneity bias.

5.1.1 Wage earners

The results from Heckman selection show for both full sample and low educated sample of wage earners, the existence of selection. Indeed, lambda is significant for these two samples. All variables in the full sample are significant. We have our variables of exclusion that are significant (married, other matrimonial status and disabled) and for the low educated sample. For both samples, the restricted variables have a negative coefficient as expected. So being disabled or married/single might determine the entry into the labor market. For the earnings equations, all variables have significant impacts, except private for the low educated sample. Age have a positive effect on earnings, and men have, on average, 81.4 percent and 90.6 percent higher earnings than women for respectively full sample and low educated sample. On average, education has a low and positive (0.6 percent) impact on earnings for the full sample and a negative impact (-5.7 percent) for the low educated sample. We can explain this negative impact for the low educated sample by the fact that a low level of education is correlated with low earnings. For the full sample, the formal vocational education has around two time more impact (84.7 percent against 45.2 percent) than the informal vocational education on earnings. That might be explained by the fact that employers are more confident in formal vocational education that is able to deliver certificate. Also living in rural area or working in informal labor market impacts negatively the earnings, respectively -60.2 percent and -18.2 percent. The

[4]For more details, see Gunther and Launov (2012)

low wages in the informal labor market and in the rural area might explain these results. Unlike the full sample, in the low educated sample, informal skills have more impact than formal vocational education (53.9 percent again 50.6 percent). We might explain that by the fact that, people who are low educated are often involved in the informal sector and there, the skill in the art acquired by on-the-job training might be more valued. It is corroborated by findings from Grootaert (1990). He found in Ivory Cost that informal vocational education has the most effects on earnings in the informal sector. Also, working in informal labor market impact negatively the earnings (-59.8 percent). Rural area is not significant for the low educated. That means that with a low level of education, working in the rural area or in the urban area does not make any difference for the earnings.

After the results from the Heckman selection framework for wage earners, we are going to give the results from IV estimation strategy in order to see if tackling both selection bias and endogeneity bias give different results. Firstly, for the full sample the coefficient of the Mills ratio is not significant. Therefore, there is not evidence of sample selection bias. But for the low educated sample, the mills ratio is significant, showing evidence of sample selection bias. When we take into account both selection bias and endogeneity bias, informal skills have not significant impact for the full sample, and the formal vocational education decreases from 84.7 percent to 37.5 percent. As we can see, for the low educated sample, informal skills have a significant impact as formal vocational education (74.1 percent again 73.7 percent). So, these results from the IV estimation strategy reveal that for those wage earners who are low educated informal and formal vocational education have a significant impact and no matter whether it is formal. Indeed, as we said above, for low educated people maybe the informal skills is most appropriate than the formal skills.

5.1.2 Independants

Selection and instrumental variable estimation

As outlined earlier, the findings of the role of human capital on the earnings of the self-employed should be treated with precaution[5]. We will have just an insight into the effects of different types of skills on earnings. For both full sample and low educated sample, we have a significant lambda, that means there is an evidence of sample selection bias. Also, we have our variables of restriction that are significant, but unlike for wage earners sample, only disabled has a negative coefficient. The value of the coefficients for the variable sex is roughly the same for both full sample and low educated sample. For the former, it is 60.6 percent, and for the last it is 61.2 percent. That means for the independents a man earn more than a woman. The variables age and age squared are only significant for the sample of low educated, but the effects are small (0.75 percent and -0.1 percent). It is not a surprise because when you are independent, you don't have an age of retirement or age of entry, it depends only on your will. Working in the informal sector and living in rural area impact negatively the earnings both for the full sample and for the low educated sample. It is the same result for the wage earners sample. So, either you are wage salaried or independents, these variables impact negatively the earnings. Working in an industry that is different from the primary sector gives more significant impacts on earnings. It might be explain by the fact that in Senegal agricultural activities are less productive. To be involved in the private sector give more significant results on earnings. For our variables of interest in this study it seems that informal skills have a small and little significance effect (6.5 percent) for the full sample and no effect for the low educated sample. The formal vocational education has significant impacts on earnings for both full sample and low educated sample, respectively 23.1 percent and 24.7 percent. In order to better understand these results, we will look at the results from the IV estimation strategy after taking into account both selection bias and endogeneity bias. Unlike for wage earners sample, the inverse of mills ratio is significant for the two samples,

[5]We have not estimated the earnings from work. The earnings reported are mixed income

showing evidence of selection bias. But informal skills and formal vocational education are not significant for the full sample and the low educated sample. These results might be explained by the fact that in the independent sample the majority are working in agricultural activities (53.42 percent) and in retail trade 26 percent. In these activities, vocational education hasn't much importance. Indeed agricultural activities are not modern, they use often ancient tools and knowledge, and in retail trade, you don't need particular skills. They need more financial literacy in order to manage better their activities. But as we said above, we have to be aware that we have mixed income for the independents.

Mixture of regression estimation

We have chosen the model with two segments based on the literature. As previously noted, in the literature on self-employment, two main segments are distinguished self-employment with growth potential and self-employment without any growth potential (business survival)[6]. the reported estimates are restricted to the sample of low educated self-employed working on non agricultural-activities. This restriction is due to the fact that the variables used as concomitant variables are only available for non agricultural activities.

The estimates show that in the first segment, our main variables of interest (informal skills and formal skills) are both significant and positive at most 5%. Although, the informal skills have fewer effects on the logarithm of the earnings (19% against 25%). In contrast, in the second segment, only formal skills are significant at 10% for the self-employed. The variables sex, experience and education are significant at a level of 5% and positive in both segments. The analysis of the probabilities shows that there is more than half of the self-employed that belong to the segment where both informal skills and formal skills have an effect on the earnings. The characteristics of the business such as access to electricity, access to credit the last 12 months and innovation the last 3 years are used as concomitant variables. These variables are chosen because they might play an important role in distinguishing self-employed which have growth potential from those without growth potential.

Among our concomitant variables, only access to credit is significative with a negative coefficient, which means that having access to credit the last 12 months decreases the probability to belong to the segment where informal skills have an effect. Otherwise, access to credit determines the belonging to the segment where only formal skills work. In the literature, access to credit is often associated with business growth (Goedhuys and Sleuven, 2010; Olawale and Garwe, 2010). This result could mean that in firms with growth potential informal skills is not enough to positively affect the revenues of the business. Indeed, growing firms need more elaborated skills than the informal skills.

6 Conclusion

Given the importance of the informal sector in developing countries and the high share of low educated people it is needed to know to what extent the informal skills are valued in the labor market. An important issue is the recognition of these skills. In this paper, we try to assess whether having formal or informal skills make any difference when you are low educated.

We use cross-sectional data, which are from the representative Survey of Monitoring Poverty in Senegal conducted in 2011. The study has shown that after controlling the endogeneity bias related to the different kind of skills, whether you have formal or informal skills does not make any significant difference on earnings when you are low educated. For low educated wage earners, both formal and informal skills have a significant effect on earnings without significant differential impact. This might be explained by the fact that low educated people are mostly

[6]We have run the Bayesian criterion (BIC) and the Consistent Akaike criterion (CAIC) with an homogenous self-employment and a two segmented self-employment and the last one minimizes these criterions

involved in low paid job. While in these kinds of jobs, practical knowledge is more rewarded. However, this result holds only for wage earners. For self-employed, informal skills and formal skills are not significant at all for low educated people. One of the explanations could be the main sectors where self-employed are, such as agriculture and retail trade. In these activities vocational education hasn't much importance. Indeed agricultural activities are not modern, they use often ancient tools and knowledge, and in retail trade, you don't need particular skills. They need more financial literacy in order to manage better their activities. But we need to be aware that the estimations are made on the mixed incomes from self-employment. A further investigation with a finite mixture regression of the effects of informal and formal skills for self-employed involved in non agricultural activities shows interesting results. The segmentation of the self-employed between two segments shows that informal skills have an effect only on one segment and that segment might be those who are running a business survival without growth potential. Indeed, having access to credit is negatively correlated with the belonging to that particular segment. At some point self-employed with growth potential need more elaborated skills acquired through the formal system.

The implications for policy design are multiple. For wage earners, instead of focusing on the recognition of the informal skills as the main tool for increasing the earnings of low educated people, the accent should be put on increasing the productivity of the informal sector where they are often involved. Furthermore, even the formal skills given to low educated people should be redesigned to fit well the needs of the labor market. In the case of the self-employed, skills on management and finance could be more useful. Further research could focus to what extent families' networks interact with these kinds of skills on the probability to experience upgraded labor mobility.

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Appendix

Table 2: Table of variables

Variable name	Definition	Nature
Logearning	Monthly earning of the main activity	Continuous
Sex	Sex of individual	Dummy (homme=1)
Age	Age of individual	Continuous
Age2	Squared age of individual	Continuous
Married	Married status	Dummy (yes=1)
Single	Single status	Dummy (yes=1)
Other marital status	Other marital status	Dummy (yes=1, reference)
Informal skills	Informal vocational education	Dummy (reference)
Formal skills	Formal vocational education	Dummy
No vocational skills	No vocational education	Dummy
Education	number of years achieved with success	Continuous
Handicap	Disability of the individual	Dummy (yes=1)
Rural	Rural or urban area	Dummy(rural=1, urban=0)
Alphabetisation	Literacy of the individual	Dummy (yes=1)
Experience	Number of years in the current and main activity	Continuous
Experience2	Number of years squared in the current and main activity	Continuous
Informal	Informal sector	Dummy(informel=1 formel=0)
Worker	Employee/work people	Dummy(yes=1
Independent	Self-employed with own business	Dummy(yes=1, reference)
Other employment status	Other Socio-professional category	Dummy (yes=1)
Private	Private or public sector	Dummy (private=1, public=0)
Primary	Primary industry	Dummy (yes=1, reference)
Secondary	Secondary industry	Dummy (yes=1)
Tertiary	Tertiary industry	Dummy (yes=1)
Other	Other industry	Dummy (yes=1)

Table 3: Heckman estimation results : wage earners

	Whole sample		Low educated sample	
lrevenu	Coef.	Std. Err.	Coef.	Std. Err.
Logearning				
Sex	0.814***	0.040	0.906***	0.068
Age	0.119***	0.007	0.216***	0.016
Age2	-0.001***	0.000	-0.002***	0.000
Education	0.006**	0.003	-0.057***	0.008
Informal skills	0.452***	0.043	0.539***	0.063
Formal skills	0.847***	0.051	0.506***	0.060
Experience	0.010***	0.002	0.007*	0.004
Experience2	0.000***	0.000	0.000	0.000
Informal	-0.602***	0.025	-0.598***	0.038
Secondary	0.365***	0.020	0.230***	0.034
Tertiary	0.465***	0.018	0.327***	0.033
Other	0.363***	0.019	0.277***	0.035
Private	-0.129***	0.030	0.155**	0.056
Rural	-0.182***	0.027	-0.023	0.051
_cons	7.094***	0.216	5.120***	0.405
selection equation				
Married	-0.114***	0.015	-0.266***	0.026
Other status	-0.105***	0.027	-0.185***	0.052
Handicap	-0.455***	0.026	-0.325***	0.049
Sex	0.739***	0.010	0.739***	0.017
Age	0.128***	0.001	0.193***	0.003
age2	-0.002***	0.000	-0.002***	0.000
education	-0.047***	0.001	-0.080***	0.004
Informal skills	0.848***	0.019	0.751***	0.028
Formal skills	0.914***	0.023	0.384***	0.039
Rural	0.468***	0.010	0.563***	0.017
_cons	-2.952***	0.023	-3.749***	0.040
mills				
lambda	0.730***	0.075	1.101***	0.117
rho	0.681		0.869	
sigma	1.073		1.267	
#Observations	102517.000		45323	
Wald chi2(14)	20904.970		3716.620	
Prob chi2	0.000		0.000	

*10% **5% ***1%

Table 4: IV estimation results : wage earners

	Whole sample		Low educated sample	
Logearning	Coef.	Std. Err.	Coef.	Std. Err.
Informal skills	0.137	0.142	0.741**	0.338
Formal skills	0.375**	0.180	0.737*	0.401
Education	0.045***	0.009	-0.016	0.024
Sex	0.451***	0.129	0.903***	0.317
Age	0.060***	0.022	0.173***	0.051
Age2	-0.001*	0.000	-0.002***	0.001
Experience	0.012***	0.002	0.006	0.004
Experience2	0.000***	0.000	0.000	0.000
Informal	-0.548***	0.026	-0.608***	0.039
Secondary	0.366***	0.021	0.212***	0.035
Tertiary	0.465***	0.019	0.315***	0.034
Other	0.368***	0.020	0.268***	0.037
Private	-0.092***	0.032	0.148***	0.055
rural	-0.357***	0.081	-0.032	0.196
imr	0.056	0.257	1.151*	0.601
_cons	8.867***	0.716	5.522***	1.692
#Observations	27833		8944	
Wald chi2(15)	27760.73		6888.49	
Prob chi2	0.000		0.000	
R-squared	0.5014		0.4353	

*10% **5% ***1%

Table 5: Heckman estimation results : Independants

	Whole sample		Low educated sample	
Logearning	Coef.	Std. Err.	Coef.	Std. Err.
Sex	0.606***	0.043	0.612***	0.080
Age	0.013	0.010	0.075**	0.030
Age2	0.000	0.000	-0.001***	0.000
Education	0.035***	0.005	0.034***	0.012
Informal skills	0.065*	0.037	0.096	0.066
Formal skills	0.231***	0.057	0.247***	0.080
Experience	0.008***	0.002	0.020***	0.005
Experience2	0.000**	0.000	0.000***	0.000
Informal	-0.605***	0.070	-0.620***	0.126
Secondary	0.628***	0.036	0.754***	0.066
Tertiary	0.740***	0.025	0.824***	0.054
Other	0.485***	0.037	0.629***	0.071
Private	0.791**	0.326	0.725	0.521
Rural	-0.602***	0.035	-0.549***	0.085
_cons	9.589***	0.453	7.900***	0.948
Selection equation				
Married	0.338***	0.019	0.249***	0.033
Other status	0.293***	0.029	0.287***	0.057
Handicap	-0.396***	0.026	-0.357***	0.059
Sex	0.762***	0.013	0.601***	0.024
Age	0.146***	0.002	0.195***	0.004
Age2	-0.002***	0.000	-0.002***	0.000
Education	-0.053***	0.002	-0.065***	0.005
Informal Skills	0.443***	0.023	0.367***	0.037
Formal skills	0.176***	0.035	0.210***	0.051
rural	0.464***	0.012	0.587***	0.023
_cons	-4.066***	0.031	-4.604***	0.061
mills				
lambda	-0.436***	0.083	-0.106***	0.185
rho	-0.361		-0.093	
sigma	1.206		1.131	
#Observations	93810		40606	
Wald chi2 (14)	6192 .51		1667.63	
Prob chi2	0.000		0.000	

*10% **5% ***1%

Table 6: IV estimation results : independents

	Whole sample		Low educated sample	
Informal skills	0.078	0.066	-0.159	0.162
Formal skills	0.087	0.129	-0.177	0.191
Education	0.066***	0.010	0.174***	0.044
Sex	0.445***	0.074	-0.018	0.229
Age	-0.022	0.018	-0.072	0.056
Age2	0.000	0.000	0.001	0.001
experience	0.009***	0.002	0.021***	0.005
experience2	0.000***	0.000	0.000**	0.000
Informal	-0.563***	0.072	-0.599***	0.129
Secondary	0.604***	0.037	0.772***	0.070
Tertiary	0.739***	0.025	0.836***	0.055
Other	0.474***	0.038	0.644***	0.075
Private	0.819**	0.329	0.765	0.533
Rural	-0.699***	0.055	-0.949***	0.162
imr	-0.749***	0.153	-1.247***	0.433
_cons	10.607***	0.635	11.943***	1.675
#Observations	19085		4210	
Wald chi2(15)	7075.45		2189.81	
Prob chi2	0.000		0.000	
R-squared	0.2694		0.3246	

*10% **5% ***1%

Table 7: Mixture regression:Independants

	Segment1	Segment2
	$\pi = 0.505$	π =0.494
Sex	0.561***	0.837***
	(0.0377)	(0.0557)
Age	0.00611***	0.00343
	(0.00172)	(0.00263)
Experience	0.00876***	0.0203***
	(0.00247)	(0.00344)
Secondary	0.0217	-0.226**
	(0.0527)	(0.0781)
Other	-0.470***	-0.135
	(0.0529)	(0.0805)
Private	0.368	0.202
	(0.492)	(0.685)
Rural	-0.177***	-0.408***
	(0.0468)	(0.0651)
Informal skills	0.197***	-0.0902
	(0.0557)	(0.0798)
formal skills	0.250**	0.258*
	(0.0850)	(0.130)
Education	0.0422***	0.0677***
	(0.00752)	(0.0105)
imr	-126.6***	-75.66*
	(29.95)	(35.73)
_cons	9.542***	10.06***
	(0.496)	(0.697)
Concomitant		
Electricity	0.212	
	(0.162)	
Credit	-0.648*	
	(0.293)	
Innovation	-0.697	
	(0.430)	
_cons	0.311***	
	(0.0181)	
N	8752	

*10% **5% ***1%