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Education, Internal Remittances and Safety Nets in Africa: Some Evidence[1]

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ABSTRACT

This paper uses LSS data from Cote d'Ivoire and Ghana to investigate the effects of education on social safety nets proxied by internal migrant remittances in Africa. We find that education has positive and statistically significant effect on the probability of sending as well as of the ***amount*** *of remittance. The estimates are robust to model specification, data organization, and estimation method. The results suggest that one mechanism through which education provides a social safety net in Africa is the migration and remittances channel. Our results suggest that investment in education may not only accelerate economic growth in Africa, it may also provide a social safety net for the population.*

***Key words*: Education, Africa, Internal Remittance, Safety Nets**
JEL: O, O55, F35, F43

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INTRODUCTION

This paper uses Ghana Living Standards Survey (GLSS) and Cote d'Ivoire Living Standards Survey (CLSS) data to investigate a mechanism through which education provides a social safety net, in the sense of Townsend (1995) and Nyarko and Gyimah-Brempong (2010), in African countries— migration and remittances. We combine cross sectional and pseudo-panel estimates to investigate the effects of education on the *probability* of sending a remittance and on the *size* of remittance conditional on sending one. We focus on internal remittance in this paper because it affects the largest number of remittance recipients in African countries even though it is often ignored in the literature.[1] This neglect implies that a major aspect of safety net is ignored in analysis and discussions of poverty in Africa. While some researchers argue that educated people remit more (Bollard *et al* 2009), others argue the opposite (Niimi *et al* 2009). This paper contributes to that debate.

We find a positive and statistically significant effect of education on the *probability* of sending a domestic remittance as well as the *amount of remittance* sent in both Cote d'Ivoire and Ghana. The estimates are robust to model specification as well as estimation method in both countries. To our knowledge, this the first paper that analyzes the effects of education on social safety nets through internal remittances.

The rest of the paper is organized as follows: The next section sketches out the empirical model we estimate, provides a brief description of the data as well as the estimation method. We make a distinction between the effects of education on the *probability* of sending a remittance (*premit*) and on the *amount* of remittance sent (*remit)* conditional on sending a remittance. Section 3 presents and discusses the statistical results while section 4 concludes the paper.

EMPIRICAL MODEL

Nyarko and Gyimah-Brempong (2010) sketch out three mechanisms through which education provides a social safety net in African countries. First, education increases the level and stability of incomes of educated people, hence providing a safety net for educated people themselves. Second, educated people have opportunities to migrate, earn higher and stable incomes, and send remittances to support household members left behind, thus providing a social safety net to those people left behind. Third, educated people are more likely to educate their siblings and other members of their families, thus reducing the inter-generational transmission of poverty—a sort of dynamic social safety net. We note that the social safety net provided by education is not limited to the income channel, and include, but not limited to, health, sanitation, distribution of political power, and other forms of freedom.

The first channel has been investigated and confirmed by labor economists and those who investigate returns to education.[2] The last two channels—remittance, especially internal remittance, and investment in children's education channels are less investigated. However, these (especially the link between education, international migration and international remittances) are the subjects of very active research in the literature (Adams: 2011). This study focuses on the effects of education on social safety nets through internal remittances. The data set available allows us to conduct a limited investigation of the remittances channel, focusing on *premit* and the *amount* of remittance (*remit*) as functions of the level education of the sending household and other conditioning variables.

Education of senders can affect remittance in two ways: It can influence the probability of sending a remittance, and conditional on sending remittance, it can affect the size of remittance sent. We estimate the following equation for the probability of sending a remittance:

$$premit = pr(educ, \mathbf{X}) \tag{1}$$

where *premit* is the probability of sending remittance, *educ* is the educational attainment of the sender and **X** is a vector of control variables. The variables contained in **X** include income, age, gender of the sender, and geographical location among others. Some researchers (e.g. Niimi *et al* 2009) argue that the probability of sending a remittance, especially from international migrants decreases with the level of education of migrants. Other researchers (e.g. Bollard *et al* 2009) contend that the opposite is true and that highly educated people tend to remit more.

Educated people may send remittance to repay student loans, as an obligation to help family members back in home communities to smoothen out consumption or provide some safety nets arising out of informal insurance contracts (Azam and Gubert: 2006, Amuendo-Durantes and Pozo: 2006). On the other hand, it may be easier for international emigrants to sever ties with household members in "home" country because they have a greater chance to be accompanied by their immediate family on international migration, hence reducing the probability of sending remittance.

The argument above regarding international migrants and remittances may not apply to internal migrants. Because internal migrants can be easily reached by their relatives, it is not easy to ignore pleas for familial support even if one was inclined to do so. Second, in Africa without formal social safety net programs, adult children provide the social safety net for aged parents and young extended family members. Internal migrants cannot easily escape this responsibility since they can be easily reached by their relatives left at home and the stigma of neglecting their poor relatives will be much stronger than for international migrants. The required support depends on the ability to pay which in turn is a function of the level and stability of incomes. Given that educated people tend to earn higher and more stable incomes, they are expected to shoulder most of the burden of upkeep of their elderly parents. Finally, educated people are *expected* to finance the education of younger siblings as investment in education is seen as an inter-generational contractual obligation (Azam and Gubert: 2006). These arguments suggest that educated internal migrants in Africa are more likely to send remittances to their families.

It is possible for education to have an impact on the *probability* of sending remittance but not on the *amount* sent; the reverse could also be true. Therefore in addition to the *premit* equation, we estimate a remittance amount (*remit)* equation. We note that the general form of this equation is:

$$remit = remit(educ, \mathbf{Y}) \qquad (2)$$

where *educ* is education of the sender, and **Y** is a vector of variables that influence the *amount* of remittance sent. While there may be common elements of **X** and **Y** in the *premit* and *remit* equations, not all elements of **X** and **Y** are common. The variables contained in the **X** and **Y** vectors include household income, age and gender of the household head, household size, number of adult workers, and location. For lack of theoretical guidance, we choose the probit functional form for the *premit* equation while a linear (in parameters) functional form is chosen for the *remit* equation. In this simple formulation, we expect the coefficient of *educ* to be positive.

The equations we estimate are given as:

$$(premit = 1/\mathbf{educ}, \mathbf{X}) = \alpha 1 educ + \alpha 2 workers + \alpha 3 totincome + \alpha 4 agehead + \alpha 5 ageheadsq + \alpha 6 gender + \alpha 7 madults + \alpha 8 loc + \alpha 9 hhz + E \qquad (3)$$

$$remit = \beta 1 educ + \beta 2 totincome + \beta 3 agehead + \beta 4 ageheadsq + \beta 5 gender + \beta 6 loc + \beta 7 hhz + \varepsilon \qquad (4)$$

where *educ* is the education of sender, *workers* is the number of workers in a household, *totincome* is total household income, *agehead* is the age of household head, *gender* is the gender of the household head, *madults* is the number of male adults in a household, *loc* is location defined as whether a sender is located in an urban or rural area, and *hhz* is household size.

DATA

The GLSS and CLSS data sets do not provide information on individual migrants and their history, education levels, or the characteristics of remitters or on remittances sent by individuals but provide information on remittance *sent by households.* We therefore conduct the analysis at the household level. The data contains information on *whether* a household sent a remittance as well as the *amount* of remittance sent (remittance expenditure), educational level of the remitting household head, household income, as well as other socioeconomic characteristics of the household.

The data comes from Waves 3 to 5 of GLSS and Waves 1-4 of CLSS. Both are large, nationally representative surveys of living standards in both countries. GLSS1 was conducted in 1987/1988 and GLSS5, with a sample size of 8,687 households, was conducted in 2005/2006. Each succeeding wave of GLSS covered more households as well as provided more detailed and comprehensive information about the living standards of Ghanaian households than previous ones. The first wave of the CLSS was conducted in 1985 and the last in 1988. Wave 1 of the CLSS sampled 1588 households while the next three waves sampled 1600 households. Unlike the GLSS, the CLSS is a rotating sample with 50 percent of households in each wave re-sampled in the next wave while the other 50 percent is rotated out.

The dependent variables are the *probability* of sending a remittance and the *amount* of remittance households send. We measure remittance as the monetary value of the sum of cash and non-cash remittances sent by a household in a year. Remittance could either be paid to domestic recipients (within the country) or international recipients (outside the country).[3] Remittance as measured here refers to domestic remittances paid by a household. We measure *premit* as equal to 1 if a household made remittance payments in a year, zero otherwise while *remit* is the total amount of remittance a household sends in a year.

For the GLSS data, we measure education as the highest level of education attained by the household head (*eduhead*). *eduhead* is coded as follows: none = 0, primary = 1, technical, vocational = 2, secondary, teacher training A & B = 3, SSCE, GCE A level, teacher training post sec = 4, polytechnic = 5, bachelors = 6, masters = 7, doctorate = 8, while for the CLSS data, *eduhead* is the highest diploma attained by the household head. *age* is the age of household head (in years), (*ltotincome*) is the log of total household income, *gender* equals 1, if the household head is male, zero otherwise, and *location* equals 1 if household is located in a rural area, zero otherwise, household size (*hhsize*) is the total number of people in a household, and all other variables are as defined in the text above. We use both cross-section data sets from wave 4 of CLSS and wave 5 of GLSS as well as pseudo-panel data constructed from all waves of CLSS and waves 3-5 of GLSS to estimate the equations.[4]

Sample statistics of the cross-section data, divided into remitting and non-remitting households are presented in table 1. Panel A presents summary statistics of some variables in the GLSS5 data while panel B presents similar statistics for the CLSS88 data. About 41.2% and 40.2% of households in the GLSS and CLSS samples respectively sent remittance.

There are differences in the characteristics of remitting and non-remitting households in the sample. Remitting households tend to be more educated, younger, wealthier, and have smaller households than non-remitting households. Besides the cross section data, we also follow Deaton (1985) and create pseudo-panel data sets from GLSS3-5 and CLSS data sets for estimation of the equations. For the GLSS, we create cohorts cells based on 6 birth year bands, 10 regions and two genders giving us 120 cohort cells for each wave for a total of 360 (120 x 3) cells. We follow a similar approach and create a pseudo-panel with 200 (50 x 4) cohort cells using the CLSS data.

ESTIMATION METHOD

If education and all elements of **X** and **Y** are exogenous, (3) and (4) could be estimated with a simple probit (or logit) and a least squares estimator respectively. However, it is possible that the same personal characteristics that determine educational attainment and income as well as migrant status also determine one's propensity to send remittance as well as the amount of remittance hence making these variables endogenous in (3) and (4). If there are valid instruments for *educ* and *totincome*, one can estimate these equations using instrumental variables (IV) estimator.

We do not have appropriate instruments, hence we estimate (3) with a control function (CF) estimator of a binary response variable like those suggested by Blundell and Powell (2004), Rothe (2009) and Dong (2010), and (4) by an IV probit estimator. The CF approach estimates a reduced form of the endogenous regressor using a non-parametric or a semi-parametric estimator and include the error term from the non-parametric estimates ($\hat{U}$) as an added regressor in the structural equation. This regressor controls for endogeneity, and the "t" statistic on its coefficient acts as a test for endogeneity in the structural equation. The advantage of this estimator is that one need not specify the statistical distribution of the error terms. In our application, we use the local linear kernel estimator (Li and Racine: 2007) in the CF estimation. We also use an instrumental variable probit (ivprobit) estimator to estimate the *premit* equation and compare the results with those of the CF estimates.

We do not know the nature of the statistical distribution of the error terms hence we use an instrumental variable GMM estimator (IVREG GMM) to estimate the *remit* equation. The use of GMM reduces the need to specify the statistical distribution of the error term and count on asymptotic distribution of such error terms. Because identification crucially depends on the strength of the instruments used in estimation, we use a battery of tests to test for the validity and strength of our instruments.

RESULTS

In estimating equations 3 and 4, we log transformed all continuous variables. The results are presented in tables 2 and 3. Columns 2—5 of table 2 present the marginal effects for *premit*. Columns 2 and 3 present the probit and CF equations for the GLSS data respectively while columns 4 and 5 present the estimates based on the CLSS data. Columns 2 and 3 of table 3 present the estimates of the *remit* equation based on the pseudo panel data for GLSS and CLSS respectively while columns 4 and 5 present the estimates based on GLSS5 and CLSS88 respectively. In the probit estimates, we treat *eduhead* and *totincome* as endogenous and use the wage rate, its square, as well as the number of male adults in the household as instruments. The regression statistics indicate a reasonably good fit for the data in all the estimates. We reject the null that all slope coefficients are jointly equal to zero at α = .01 and the average predicted probability of remittance is very close to the actual probability of remittance in the sample.

premit

The marginal effect of *eduhead* in columns 2—5 is positive and statistically significant at α = .01 suggesting that education of the household head positively affects the probability that a household sends remittance, all things equal. The marginal effect of *eduhead* ranges from 0.06 to 0.10 depending on the sample and estimation method. This positive marginal effect is consistent with the results of research that finds a positive relationship between education and remittances (Bollard *et al* : 2009) but inconsistent with research that finds negative relationship between education and remittance (Niimi *et al*: 2009). The marginal effects of the other regressors have the expected signs and significantly different from zero at α = .05 or better. In particular, the marginal effect of household income, age of the household, and urban location are positive while the marginal effects of household size and number of male adults are negative and significant.

The marginal effect of *eduhead* in the CF estimator, presented in columns 3 and 5, is positive, statistically significant, and *qualitatively* similar to their IV probit estimator counterparts. This suggests that the effect of education on the probability of sending an internal remittance does not depend on the estimation method used. The coefficient of $\hat{U}$ in column 3 is significant at α = .05 suggesting that education is endogenous in the *premit* in the GLSS data; however, it is insignificant in the CLSS data (column 5) suggesting that education of the household head could be treated as exogenous in the CLSS sample.

remit

Estimates of the *remit* equation are presented in table 3. Columns 2 and 3 present the estimates based on the pseudo-panel data constructed from the various waves of the Living Standards Measurement Surveys, while columns 4 and 5 present the estimates based on GLSS5 and CLSS88 respectively. χ^2 test of endogeniety suggests that indeed both total income and *eduhead* are endogenous. Tests of instrument validly, instrument strength, and over-identifying restrictions as indicated by the Sargan test, Klienberg-Paap LM test, Hansen *C* test, and the first stage $\mathbf{R}^2$ suggest that the instruments we used are "strong" instruments. Regression statistics show that the model fits the data reasonably well.

The coefficient of *eduhead* is positive and significant in all columns of table 3 at $\alpha = .05$. The elasticity of remittance with respect to *eduhead* ranges from 0.3 (GLSS5) to 1.42 (CLSS88). The positive and significant coefficient of *eduhead* is consistent with studies that find that educated people remit more than less educated people, all things equal (e.g. Bollard *et al*: 2009, Mazzucato: 2009) but inconsistent with results that find negative or no relationship between education and remittance (e.g. Niimi *et al*: 2009). The coefficient estimates of the control variables are of the expected signs and most are statistically significant at $\alpha = .05$.

Our results should, however, be interpreted with caution. We are only able to identify education and income of households that send remittance; we are not able to investigate who *receives* the remittance sent. We do not investigate the relationships among education, *international migration*, remittances, and social safety nets. Given the increasing importance of international migration of young educated people in Africa and the fact that the average amount of international remittance dwarfs that of domestic remittance, international remittance as a source of social safety net may be more important than internal remittances.

CONCLUSION

We use GLSS and CLSS data to investigate how education provides social safety nets through internal remittance in Africa. We find that education independently influences the probability of, and the size of remittance that households send. This effect is robust to estimation method and sample. The results are consistent with the result of previous research that finds that education is positively and significantly related to remittances, all things equal. The results are consistent with the theoretical model sketched out in Nyarko and Gyimah-Brempong (2010) and suggest that expenditure on education may be the ultimate social safety net in African countries. Our results are consistent with studies that find positive relationship among education, international remittances, and social insurance in developing countries (Bollard *et al*: 2009, Azam and Gubert: 2006, Mazzucato: 2009, and Yang and Choi: 2005, Sharma: 2009, among others).

Our result have some development and welfare policy implications for African countries. It suggests the importance of education as a mechanism for providing social safety net through transfers (remittances) from educated people. Increasing education at all levels will provide a longer lasting social safety net than possibly cash transfer would. The policy implication is that African countries should increase investment in education as a means to provide social safety nets. The results also suggest the need for policy to improve the mechanisms for sending and receiving remittances, whether domestic or international.

NOTES

1. We use "domestic remittance" and "internal remittance" interchangeably to refer to remittances from within the borders of a country rather than a cross border remittance which we refer to as "international remittance".
2. Instrumental variables estimation using our data confirms that indeed higher education is associated with higher incomes, all things equal.
3. For example, a large amount of remittances from Cote d'Ivoire and Ghana are sent to recipients in Burkina Faso, Mali, and Niger.
4. We could not use the first two waves of GLSS in constructing the pseudo panel data because it did not have detailed information about remittance and other socioeconomic variables used in constructing the data.
5. A test of endogeneity of *eduhead* and *ltotincome* in the CLSS data does not reject the null hypothesis of exogeneity so we do not use other estimators besides least squares for this data set.

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Table 1: **Characteristics of Remitting and Non-Remitting Households**

Variable	Remitters	Non-Remitters	Difference
	Panel A	**GLSS**	
hhsize	3.8328	4.7488	-0.916***
totalincome (Cedis)	1,340,000.00	1,060,000	280,000
agehead	43.67	44.918	-1.248
eduhead	3.54	3.14	0.40*
postsecondary	0.098	0.069	0.29***
maleadults	1.21	1.087	0.13
workers	2.14	1.94	0.20
remittance (Cedis)	253,263	0	253,263
	Panel B:	**CLSS**	
hhsize	7.45	8.89	-1.44***
totalincome (CFAF)	1,757,730	1,172,248	585.482**
agehead	42.81	48.22	-5.41
eduhead	1.1372	0.693	0.444**
maleadults	2.42	1.67	0.75**
migrants	4.48	3.93	0.55
workers	2.99	2.10	0.89***
remittance (CFAF)	90,358.43	0	90,358.43

* 2-tail significance at $\alpha = 0.05$ *** 2 tail significance at $\alpha = 0.01$

Table 2: **Estimates: *premit***

	2	**3**	**4**	**5**
eduhead	0.0650***	0.0827***	0.1051	0.1067
lworkers	0.1377**	0.1801***		
ltotincome	0.1658***	0.1417	0.1027	0.0963
agehead	4.0739***	4.0039	2.1853***	2.0778
ageheadsq	-0.5492***	-0.5399	-0.3176***	-0.3029
gender	0.1036***	0.1036	-0.1332***	0.2663***
maleadults	-0.0242**	-0.0658	-0.06114***	-0.1278
loc	0.0731***	0.0727	-0.0521***	-0.0412
hhz	-0.0662***	-0.0658	-0.0631***	-0.0576
ˆ		0.0833**		0.4281
Predict	0.896	0.912	0.89	0.90
LR χ^2	274.68	278.95	184.34	191.28
F	86.29			
Pseudo R^2	0.18	0.21	0.08	0.09
χ^2 **test of Endog.**			2.01	1.89

+ absolute value of asymptotic "z" statistics in parentheses.

*2-tail significance at α=0.10

**2-tail significance at α=0.05 ***2 tail significance at α=0.01

Table 3: **Estimates of *remit* Equation**

Variable	**Coefficient**		**Estimates**	
	PSEUDO	*PANEL*	*CROSS*	*SECTION*
	GLSS	CLSS	GLSS5	CLSS88
eduhead	1.3846***	1.1461**	0.1628***	1.4223***
	(3.11)	(2.04)	(2.92)	(4.15)
ltotincome	0.3211***	2.1010***	1.5495***	2.4481***
	(2.89)	(5.02)	(4.91)	(6.47)
agehead	0.2523***	5.4523***	3.82569***	6.2161**
	(3.05)	(3.05)	(4.89)	(2.50)
ageheadsq	-0.7238***	-1.1591**	-0.4927***	-0.2216**
	(3.06)	(4.22)	(4.64)	(2.73)
gender			0.0623**	1.3215***
			(2.02)	(3.28)
loc	-0.0118**	-0.0871***	-0.0320***	-0.0871***
	(1.84)	(3.82)	(4.66)	(3.19)
hhz	-0.3096***	-0.8096***	-0.1268***	-1.2277**
	(5.91)	(5.73)	(5.46)	(2.56)
constant	1.2766	-1.2489***	-7.6699**	-12.2716***
	(0.32)	(1.32)	(1.98)	(2.92)
χ^2	189.68			203.21
F	86.29	28.93	353.60	256.21
R^2	0.706	0.411	0.92	0.4452
K-P rk LM		18.72	10.98	
Sargan		0.209	0.206	0.36
Hansen C.		3.97	6.22 [4]	
Anderson			8.23 (*p*=	
First stage R^2			0.43	0.41
χ^2 **test of Endog.**			26.10	1.43 [1]

+ absolute value of asymptotic "z" statistics in parentheses.

* 2-tail significance at $\alpha = 0.10$

** 2-tail significance at $\alpha = 0.05$ *** 2 tail significance at $\alpha = 0.01$