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Skills, Schooling, and Household Income in Ghana

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This article examines the impact of cognitive skills on the income of households in Ghana. It uses scores on mathematics and English tests to measure cognitive skills and estimates the returns to these skills based on farm profit, off-farm income, and total income. The article uses Powell's censored least absolute deviations and symmetrically trimmed least squares estimators to estimate farm and off-farm income. In contrast to Heckman's two-step or the Tobit estimator, Powell's estimators are consistent in the presence of heteroscedasticity and are robust to other violations of normality. The results show that cognitive skills have a positive effect on total and off-farm income but do not have a statistically significant effect on farm income.

This article estimates the effect of cognitive skills on the incomes of Ghanaian households. Scores on mathematics and English tests are used as measures of cognitive skills, and the returns to these skills are measured by estimating farm profit, off-farm income, and total income. Three features distinguish the analysis from that in much of the human capital literature. First, it measures human capital using performance on mathematics and English tests rather than years of schooling. Second, it measures the returns to human capital by estimating total household income and its components rather than just examining wage income, as is more typically done. Third, it incorporates information about the sample design into the estimation strategy.

The choice of test scores, as opposed to years of schooling, for a measure of human capital is motivated by the argument that it is not school attendance that intrinsically increases a worker's productivity, but instead the skills obtained while in school. Following this argument, test scores serve to proxy for human capital better than years in school.[1] The use of test scores standardizes the measure of human capital across numerous schools of varying quality. Just as colleges in the United States use standardized tests to control for the variation in

1. One important caveat to this statement is that this article assumes that test scores are orthogonal to the estimated residuals. If endogeneity bias exists, there is no reason to believe that the bias is more or less of a problem for estimating returns to schooling or skills. Jolliffe (1996) tests for endogeneity bias of the estimated returns to schooling and finds that it is not significant for this sample of households.

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school quality of its applicants, so too does the use of tests control for the significant variation in school quality across Ghana.

Several factors motivate the decision to measure the returns to human capital by estimating total household income, including farm and off-farm income. The majority of the human capital literature focuses on wage income, but the large majority of households in developing economies are self-employed workers, not wage earners. World Bank (1995) provides a detailed discussion of the typical composition of labor forces in developing countries. Grigg (1991) discusses the predominance of agricultural laborers in developing countries.

Another reason to estimate total income rather than just farm profits or wage income is that a large portion of Ghanaian households earn income from numerous sources. For example, approximately 70 percent of Ghanaian households engaged in farming have at least one household member who is engaged in some form of off-farm work. Estimating the returns to human capital in just one source of income presents a skewed picture of the returns to human capital for households engaged in numerous income-generating activities. This statement assumes that labor markets are inefficient and that it is not possible for households to hire in and out labor of certain skill types. Two pieces of evidence support the assumption of incomplete labor markets. First, labor markets are not very active in Ghana. The average farming household only spends 5 percent of farm income on hiring outside labor. Second, the returns to skills vary dramatically across economic activities.

A strictly practical reason for using total household income to measure the returns to human capital stems from a feature of the data. Income data from household surveys in developing countries are measured largely at the household level, and the data typically make it difficult to attribute portions of household income to individual household members. This is because the majority of laborers work either for household farms or for nonfarm, small household enterprises. This point is supported in more detail in Jolliffe (1996).

The importance of incorporating sample design information into the estimation strategy results from the standard practice of using multistage sample designs for cross-sectional, nationally representative surveys. Multistage (or cluster-based) sample selection frequently results in the need to drop the assumption that residuals are homoscedastic. The presence of cluster-induced heteroscedasticity has two important effects. First, standard errors that have not been corrected for the sample design dramatically underestimate the correct standard errors. Second, the standard estimators used for limited dependent variable analysis including sample selection estimators are biased in the presence of heteroscedasticity.

Section I reviews the human capital literature pertaining to developing countries and the use of test scores. It begins by discussing the literature on the returns to additional years of schooling in developing countries and then covers the literature on test scores and school quality. Section II discusses the survey

and sample design and reviews the estimation strategy and results. Section III presents some concluding comments.

I. Literature Review

The literature on returns to human capital in developing countries focuses predominantly on measuring the returns to additional years of schooling for wage earners. Psacharopoulos (1985 and 1994) summarizes the results from more than 55 such wage studies from Africa, Asia, and Latin America. These summaries present a consistent pattern of very large returns to primary education and somewhat smaller returns to secondary and postsecondary education. Psacharopoulos (1994) states that the average private rate of return to primary education in developing countries is 29 percent, while the returns to secondary and postsecondary education are 18 and 20 percent, respectively. The main problem with the focus of these studies is that the majority of individuals in developing countries are not wage earners. For example, about 20 percent of working individuals in Ghana are wage earners. Similarly, wage earners make up 15 percent of the workforce in India, 19 percent in Haiti, 20 percent in Nigeria, and 11 percent in Togo (World Bank 1995: table A-2). In order to draw conclusions about the returns to education for the majority of the population, it is necessary to assume that the benefits of education to farmers and other self-employed workers are the same as those accrued by wage earners.

The largest component of the workforce in most developing countries is engaged in self-employed farm work. Examining the returns to education for these laborers results in a more representative assessment of the private value of education to the population. Jamison and Lau (1982) review the results of more than 35 studies that measure returns to the education of farmers in Africa, Asia, and Latin America. Most of these studies suggest that education has a positive effect on farm production, but the statistical significance of this result is often weak. In particular, Jamison and Lau's review finds no support for the hypothesis that there are any returns to education for farmers in Africa. The lack of a significant effect of schooling on farm profit has often been attributed to either the low technological level of production or the absence of technological change in Africa. Foster and Rosenzweig (1996) present evidence that technological change increases the returns to schooling. The contrast between the results of wage regressions and farm-profit regressions suggests that it is inappropriate to use results from one or the other to make inferences about the effects of education on the African workforce.

The remaining component of household income (at least that resulting from labor) is self-employed, off-farm income. This component has been somewhat ignored in the human capital literature, in spite of the fact that self-employed, off-farm income is at least as significant as wage income in many developing countries. In the case of Ghana, 47 percent of households generate some self-employed, off-farm income, while 36 percent of households have at least one

wage-earning member. Blau (1986) finds that urban, self-employed men in Malaysia earn substantially more than wage earners with the same characteristics. Vijverberg (1993: 2) also notes that "family enterprises with one to four workers accounted for about 70 percent of manufacturing in India and Indonesia, 60 percent in the Philippines, and 40 percent in Korea and Columbia." Soon (1987) and Vijverberg (1993) have written two of the very few papers on returns to human capital that examine self-employed, off-farm work. They both find evidence that schooling asserts a positive influence on self-employment income. Vijverberg, though, finds little evidence of returns to cognitive skills. Soon states that the returns to schooling for the self-employed are significantly lower than for wage earners. Vijverberg uses a subsample of the data used here and selects households with self-employed, off-farm income from a nationally representative sample but does not correct for the potential selection bias. By dropping more than 30 percent of the sample for various reasons, Soon also faces but does not deal with potential sample-selection bias. This problem is handled here by including all households and assigning zero self-employed, off-farm income to those not engaged in this activity.

The strategy of focusing on only one source of income (such as wage or farm income) not only potentially suffers from sample-selection bias but also ignores the fact that many households generate income from several sources. For the individual who is engaged in both farm and wage work, the returns to human capital are the benefits derived in both sectors. For this reason, this study examines total household income as well as farm and off-farm income.

A motivation for using test scores as a measure of human capital instead of years of schooling is to control for variation in school quality. Another motivation is the argument that it is not school attendance that increases a worker's productivity, but rather the skills learned. Test scores should serve as a better measure of these skills than years of schooling. This motivation is reasonable if there is evidence that school quality varies within countries and if school quality affects test score performance. Hanushek (1995) argues that school quality is an important determinant of the returns to education and that quality varies dramatically within developing countries (and the United States). Hanushek further argues that the focus of education policy should switch from increasing access to schooling to improving the quality of schooling. There is also an extensive U.S. literature on whether school quality affects the rate of return to schooling. Rizzuto and Wachtel (1980) and Card and Krueger (1992a and 1992b) use U.S. census data on location and date of birth to match individuals with state-level data on school quality. All three studies find that school quality is an important determinant of the rate of return to education. Glewwe and Jacoby (1994) examine the test performance of middle school students in Ghana and find that the quantity and quality of school attendance have an impact on test scores. Behrman and Birdsall (1983) argue that ignoring differences in the quality of schools may bias the estimated returns to schooling. They use data from Brazil to show that the estimated bias can be large.

The literature on measuring the returns to cognitive skills is significantly more sparse than the returns-to-schooling literature. Boissiere, Knight, and Sabot (1985) and Knight and Sabot (1987) use household survey data on wage earners from Kenya and Tanzania to estimate the returns to cognitive skills, as well as other issues. Boissiere, Knight, and Sabot find positive and significant returns to cognitive skills and to schooling and suggest that these results refute the screening and credentialism theories of education. Knight and Sabot show that years of schooling are an important determinant of cognitive skills and that cognitive skills are important determinants of wages.

Alderman and others (1996), using data from four districts in Pakistan, find that cognitive skills have a significant effect on rural wages. Glewwe (forthcoming), using a subset of the data used in this article, finds evidence that cognitive skills are important determinants of wages. He also shows that improvements in school quality have a higher return than additional years of schooling for wage earners. Jolliffe (forthcoming), using a different subset of the data used in this article, suggests that mathematics skills have a positive effect on the farm income of Ghanaian households, while English skills have no effect.

In contrast to papers on the returns to cognitive skills, this article examines the effect of skills on total household income and not just wage or farm income. It is not enough to know if improved skills result in higher wage or farm income because increases in one type of income could be quite different from changes in the other type. For example, if it is found that improved skills do not improve farm income, households may still benefit from improved skills because their nonfarm income has increased.

Moreover, this article recognizes the importance of sample design in the estimation strategy. The presence of design-induced heteroscedasticity requires large adjustments to standard errors and the use of estimators that are robust to the failure of the homoscedasticity assumption. Much of the literature discussed here focuses on certain types of occupations and therefore likely encounters some form of sample-selection bias. The sample selection results from either selecting farm households or wage earners from a nationally representative survey or simply from the fact that occupation is a choice variable. The papers that address the potential for sample-selection bias use the standard correction techniques, which are estimated by either a maximum-likelihood or two-step estimator. These correction techniques require homoscedastic residuals, and the existing literature relies heavily on this untenable assumption. This article handles sample selection by modeling farm and off-farm income as a type I Tobit model and uses estimators that are robust to heteroscedasticity.

II. Data and Estimation

The analysis uses data from the Ghana Living Standards Survey (GLSS), a nationwide household survey carried out by the Ghana Statistical Service with technical assistance from the World Bank. As with most household surveys, the

Table 1. *Descriptive Statistics from the Ghana Living Standards Survey, 1988–89*

Variable	*Mean*	*Standard deviation*	*Minimum*	*Maximum*
Income				
Log total income	12.6	0.62	9.98	15.03
Log farm income	6.80	5.61	0.00	13.92
Log off-farm income	11.7	2.58	0.00	15.03
Household test scores and schooling				
Maximum English score	11.9	12.5	0.00	3.70
Maximum mathematics score	11.4	9.94	0.00	4.20
Average English score	7.60	9.48	0.00	35.00
Average mathematics score	7.56	7.58	0.00	40.00
Maximum years of schooling	8.12	4.70	0.00	23.00
Average years of schooling	4.16	3.45	0.00	20.00
Farm income				
Log (acres of land farmed)	2.11	1.90	0.00	6.55
Household average log of farm experience	1.71	1.16	0.00	4.11
Cluster/zone average day farm wage	342	114	0.00	600
Regional average				
ln (price fertilizer)	7.57	0.24	7.05	7.93
ln (price insecticide)	7.09	0.51	6.19	7.85
Price of maize	5.14	2.39	2.00	15.75
Price of okra	0.67	0.34	0.20	3.20
Price of cassava	1.13	0.84	0.01	4.00
Price of pepper	2.93	0.99	0.60	5.89
Off-farm income				
Log (value of business assets)	3.90	4.41	0.00	19.60
Household maximum log (off-farm experience)	1.62	1.15	0.00	4.51
Area average off-farm wage[a]				
Type 1	0.35	0.11	0.08	0.45
Type 2	0.47	0.15	0.20	0.65
Type 3	0.75	0.25	0.39	1.09
Type 4	0.82	0.32	0.38	1.53
Type 5	2.13	1.05	0.99	3.88
Household characteristics				
Log of household size	1.34	0.70	0.00	3.64
Household gender composition[b]	1.49	0.28	1.00	2.00
Number of males				
15–24 years old	0.42	0.71	0.00	5.00
25–34 years old	0.25	0.45	0.00	3.00
35–44 years old	0.18	0.39	0.00	1.00
45–55 years old	0.14	0.34	0.00	1.00
Number of females				
15–24 years old	0.42	0.66	0.00	5.00
25–34 years old	0.34	0.51	0.00	3.00
35–44 years old	0.19	0.41	0.00	2.00
45–55 years old	0.17	0.40	0.00	3.00

Note: The sample consists of 1,388 households.

a. The off-farm wages are regional averages of wages grouped into five occupational types. Type 1 occupations are the lowest-wage activities, and type 5 are the highest. The data on wages come from the half of the sample that was not administered the supplemental education module.

b. Household gender composition is the household average value of the binary variable that takes the value of 1 for men and 2 for women.

Source: Author's calculations based on the Ghana Living Standards Survey for October 1988–September 1989.

sample is not a simple random draw but rather a two-stage sample. (For more details on the sample design, see Scott and Amenuvegbe 1989.) The survey, administered from October 1988 to September 1989, covers 3,200 households and contains detailed information on formal and informal labor activities, household farm activities, expenditures, education status of household members, and many other determinants of household welfare. Table 1 provides basic descriptive statistics of the sample used here. See Glewwe and Twum-Baah (1991) for more information.

Members from approximately half of the households, or 1,585 households, in the 1988–89 GLSS were randomly selected to be administered a series of cognitive skills tests. From this random sample, 197 households are dropped from the analysis, resulting in a sample of 1,388 households. The analysis uses data on members of these 1,388 households between the ages of 15 and 55. Adults over 55 are excluded because they were not administered the battery of tests, and children under 15 are excluded to ensure that children still in school are not treated as working adults. The large number of dropped households is due primarily to missing test score data from 163 of the households. In addition to the households dropped because of missing test score data, 31 households are dropped because there are no farm price data in their region of residence. Two households are dropped because there are insufficient data to construct an estimate of their total consumption, and one household is dropped because there are no data on school levels within the household. Jolliffe (1996) presents a detailed comparison of the sample with and without the 197 dropped households and concludes that dropping the households does not significantly alter the composition of the sample. In particular, the rural/urban distribution of the data is the same, as is the geographic distribution. Similarly, the average values of education levels, per capita expenditure, and gender and age composition of the households are essentially the same when the 197 households are dropped.

Cognitive Skills and School Attainment

In spite of ambitious literacy and education goals set during the 1960s (and largely pursued during the 1970s), school attainment for many Ghanaians is low. The GLSS data show that the average Ghanaian ages 15–55 has completed just six years of schooling, and less than 6 percent of this age category has any postsecondary education. The government of Ghana's goal of increasing the amount of schooling received by its citizens is nonetheless reflected in the data. Individuals ages 30–34 who were going to school during the late 1960s and early 1970s have on average seven years of school. This figure contrasts with an average level of four years of schooling for people ages 45–49, most of whom received their education prior to the country's independence. There is also a pronounced difference in school attainment between urban areas, where residents have on average eight years of school, and rural areas, where they average 4.6 years.

The cognitive skills tests, which consisted of two mathematics and two English comprehension tests, were administered to household members ages 9–55. Both the mathematics and English tests consisted of a relatively easy test and a more difficult, advanced test. Those who correctly answered five or more (out of eight) questions on the easy test were given the advanced test. To construct one score for mathematics skills and one for English skills, the sum of the simple and advanced tests is taken. Zeros are assigned on the advanced test to those who did not receive a score of five or higher on the easy test. Those individuals who were unable to read the tests are also assigned a zero, as are most individuals with less than three years of schooling. The fieldwork was designed for tests to be administered only to individuals over nine years of age and with at least three years of schooling. This rule was not completely followed, and about 10 percent (or 119) of the individuals with less than three years of schooling took the tests.

The test scores follow the same patterns as years of schooling attained in that they are correlated with age and residence. For those individuals ages 30–34, the average mathematics and English scores are 9.8 and 11.1, respectively. Individuals ages 45–49 scored significantly lower on both the mathematics (6.0 answers correct) and English tests (6.5 answers correct). Similarly, the average scores in urban areas were 10.8 (on the mathematics test) and 12.5 (on the English test), both of which are significantly higher than the average scores of 5.8 (mathematics) and 5.7 (English) in the rural regions.

Table 2 presents further evidence that schooling is an important determinant of the mathematics and English scores. Skills are modeled as functions of experience, schooling, and ability. Dummy variables for relationship to head of household are also included to control for any sort of gender or family-related bias resulting from position in the household. For example, dummy variables are used to designate whether the individual is a spouse, son or daughter, grandson or granddaughter, niece or nephew. These are tested for joint significance with the female dummy variable. A household-level, fixed-effects estimator is used to control partially for ability. This assumes that an important component of an individual's ability is derived from the household, whether genetically or learned. The estimates in table 2 suggest that schooling is an important determinant of test scores, even controlling for experience and household fixed effects.

One reason for using test scores rather than years of schooling is to control for variations in school quality. Table 3 presents evidence that the quality of schooling is better in urban areas than in rural regions. The percentage of classrooms in primary schools that cannot be used when it rains is 58 percent higher in rural regions than in the urban areas. Similarly, the percentage of rooms without blackboards in rural primary schools is twice as high as in urban ones. Urban teachers have more experience and somewhat more schooling.

The differences in school quality are associated with differences in student test performance, although the school quality variables were not measured when the individuals attended school. The implicit assumption is that the relative dif-

Table 2. *Determinants of Cognitive Skills, Ghana, 1988–89*

Variable	*English*	*Mathematics*
Potential experience	0.221**	0.030
	(0.1069)	(0.0829)
Potential experience squared	–0.003*	–0.001
	(0.0018)	(0.0014)
Years of schooling	0.941***	0.662***
	(0.1887)	(0.1463)
Years of schooling squared	0.051***	0.045***
	(0.0093)	(0.0072)
Interaction: school and experience	–0.005	0.003
	(0.0051)	(0.0040)
Dummy: 1 = female, 0 = male	–2.174***	–2.512***
	(0.5281)	(0.4095)
Intercept	–0.011	3.198**
	(1.8265)	(1.4163)
Adjusted R^2	0.71	0.74
Number of observations	2,295	2,295

Note: Values are fixed-effects estimates, controlling for household effects. The dependent variables are English and mathematics test scores. The 2,295 individuals come from 1,118 households that have more than one member between the ages of 15 and 55. Thirteen dummy variables for relationship to the head of household are included in the estimation, and, along with the gender dummy, they are jointly significant (p = 0.00) for both test scores. The household fixed effects are also jointly significant (p = 0.00) for both scores. Potential experience is defined as age minus years of schooling minus six. Standard errors are in parentheses.

* p-value is less than 0.1.

** p-value is less than 0.05.

*** p-value is less than 0.01.

Source: Author's calculations.

Table 3. *Measures of Primary School Quality in Urban and Rural Areas of Ghana, 1988–89*

	Urban		*Rural*	
Indicator	*Mean*	*Standard deviation*	*Mean*	*Standard deviation*
Fraction of rooms unusable when wet	0.19	0.025	0.30	0.029
Fraction of rooms with a blackboard	0.96	0.013	0.90	0.015
Teacher's average experience (years)	10.97	0.383	8.26	0.312
Average teacher's schooling (years)	12.17	0.197	11.45	0.143

Source: Jolliffe (forthcoming: table 7.1).

ference between urban and rural schools has not changed significantly over time. Urban individuals with six years of schooling scored 29 percent higher than rural individuals with the same years of schooling on the mathematics tests and 169 percent higher on the English tests. Similarly, individuals living in urban areas with eight years of schooling scored 19 and 80 percent higher than individuals in rural areas on the mathematics and English tests, respectively. The differences in school quality highlight problems of using educational attainment

as a measure of human capital. In the event that an additional year of schooling produces different skill levels across groups of individuals, using levels of schooling will systematically mismeasure human capital and thus potentially bias estimates of the returns to human capital.

Cognitive Skills and Household Income

The returns to cognitive skills accrued by households are estimated using three separate household-level income functions: total income, farm income, and off-farm income. The mathematics and English test scores are included in all models as explanatory variables. Both the household average and maximum test scores of household members ages 15–55 are used. For more discussion on these two indicators, see Jolliffe (1996); the subsection on farm profit draws heavily on Jolliffe (forthcoming).

Farm revenues are measured as the sum of the value of all crops and animal products marketed in the last 12 months, the value of crops kept for seed and given away as gifts, and the value of home-consumed food and animal products. The value of farm output, G_f, is assumed to be a function of cognitive skills and the logs of land, labor, and crop inputs. The log of the farm production function G_f can be written as:

$$G_f = G_f\,(A_f, L_f, X_f, \eta, \upsilon) \tag{1}$$

where A_f contains the log of acres of land cultivated and farming experience, both of which are treated as fixed inputs. L_f is the log of hours of household farm labor, X_f represents all other variable inputs (fertilizer and insecticide), η measures cognitive skills (English and mathematics test scores), and υ is an error term. Throughout the article, the subscript f denotes a farm variable, and the subscript o denotes an off-farm variable.

As it is typically assumed that farmers maximize farm profits, not farm revenues, expenditures on insecticide, pesticide, hired labor, seed, rented land, storage, containers, and transportation are subtracted from farm revenues. Crops given as payments for other inputs are also deducted from farm revenue. The resulting measure of farm profit is conditional on the quantity of land and labor. The average value of this conditional, or restricted, farm profit is 144,604 cedis. During the year of the survey fieldwork, inflation in Ghana was 24 percent (Ghana Statistical Service 1991a). To correct for this all values in cedis are deflated to October 1988. The average exchange rate during 1988 was 200 cedis to the U.S. dollar (Ghana Statistical Service 1991b).

Solving for the input demand functions in terms of prices and substituting them back into equation 1 results in a restricted net income function Y_f. The log of this is estimated as:

$$Y_f = Y_f\,(A_f, L_f, p_f, \eta, \mu) \tag{2}$$

where p_f is a vector of input and output prices (fertilizer, insecticide, maize,

okra, cassava, and pepper prices and farm wages), and μ is an error term. The measures of farm wages used are the wages for an adult male day laborer. Farm input and output prices are cluster averages.

Estimating farm profit rather than farm output is both more consistent with economic theory and also likely to reduce the possibility of endogeneity bias. All of the chosen levels of the variable inputs, which are elements of the farm production function, are replaced with their prices. Even when markets are not functioning perfectly, it is still reasonable to assume that prices are exogenous to the farm household's decisions. The restricted farm profit function, equation 2, still contains the quantities of land and labor. Jolliffe (1996) shows that omitting land from farm profit regressions has no effect on the estimated return to human capital and argues that this implies that land either is fixed in the short run or is orthogonal to schooling and skill variables.

The measure of off-farm income aggregates wage income and self-employment income. The decision to aggregate these two loses some information but helps to focus on the difference between farm and nonfarm income. The measure of wage income adjusts the wage rate by including all pecuniary remuneration for the labor supplied including commissions, bonuses, tips, allowances, and gratuities. The wage income is also adjusted to reflect the value of all nonpecuniary payments including remuneration in the form of food, crops, animals, housing, clothing, transportation, or any other form.

The log of off-farm income, Y_o, is modeled as:

$$Y_o = Y_o\,(A_o, L_o, p_o, \eta, \varepsilon) \tag{3}$$

where A_o contains the log of the value of business assets and off-farm work experience, L_o is the log of hours of household off-farm labor, p_o is off-farm wages, η measures cognitive skills (English and mathematics test scores), and ε is an error term.

Both the farm and off-farm income functions include hours of household labor, whose levels are chosen by the household. To correct for this potential endogeneity bias, farm and off-farm labor are modeled as functions of household size, gender and age composition of the household, and farm and off-farm income. Household characteristics enter the labor functions because it is the total household level of labor supply, not individual-level labor supply, that is being modeled. Gender composition is included because of the cultural norms that dictate that men, women, and children will typically perform different work activities. Often the activities of women and children are not picked up in the measure of off-farm work. For example, the time spent collecting firewood or preparing food is not included in the measure of total hours worked. By using farm and off-farm income as determinants of labor supply, the model treats labor markets as imperfect. This model of labor supply allows equations 2 and 3 to be rewritten as:

$$Y_f = Y_f[A_f, L_f(X_h, Y_f, Y_o), p_f, \eta, \mu] = Y_f\,(A, X_h\,, p, \eta, \mu) \tag{2'}$$

$$(3') \qquad Y_o = Y_o[A_o, L_o(X_h, Y_o, Y_f), p_o, \eta, \varepsilon] = Y_o(A, X_h, p, \eta, \varepsilon)$$

$$(4) \qquad Y = Y_f + Y_o = Y(A, X_h, p, \eta, \nu)$$

where A is the farm and off-farm fixed inputs, X_h represents household characteristics, and p is a vector of farm and off-farm prices. Total household income, equation 4, is modeled simply as the sum of farm and off-farm income and is also estimated in log form. Because the total household variable is the sum of farm profit, enterprise profit, and wage earnings, it might be more accurately described as total household earnings.

Heteroscedasticity

The two-stage design of the GLSS sample typically results in the rejection of the assumption of homoscedasticity because observations drawn from within a cluster are likely to have characteristics that are more similar than observations drawn from different clusters. This difference between intra-cluster and inter-cluster correlations will most likely result in heteroscedasticity. Examining the Kish design effect is helpful to determine if the heteroscedasticity resulting from the sample design will introduce a large bias in the estimated standard errors. The square root of this measure of intra-cluster correlation gives an upper bound to the potential bias. (See Kish 1965 for more details.) The ordinary least squares (OLS) residuals from estimating the log of total income have a Kish design effect of 2.67. This means that the standard errors from OLS estimation may need to be corrected by as much as the square root of the design effect, or increased by 63 percent.

Correcting the total income model for heteroscedasticity is fairly straightforward. OLS estimation results in consistent parameter estimates for these models, but the residuals need to be corrected following Huber (1967). The Huber correction is asymptotically equivalent to a jackknife estimate. The principle behind Huber's formula is that if the design effect is not significant, then the estimated standard error should not be affected by dropping any particular cluster. The correction employed by Huber is asymptotically equivalent to repeatedly estimating standard errors, dropping one cluster at a time until all clusters have been excluded once. The average value of these estimated standard errors is then the Huber-corrected standard error. Scott and Holt (1982) discuss the impact of sample design on the correction required for the OLS standard errors.

Heteroscedasticity introduces more problems for estimating farm and off-farm income. Both of these variables are censored at zero, and the standard estimators used for the censored model, such as the Tobit or Heckman's two-step estimator, result in biased estimators. Arabmazar and Schmidt (1981) show that the bias resulting from the Tobit estimator can be large.

Here farm and off-farm income are estimated using two estimators proposed by Powell, both of which are designed for the censored model and are consistent in the presence of heteroscedasticity. The first is Powell's (1986) symmetrically trimmed least squares (STLS) estimator. The second is Powell's (1984) censored

least absolute deviations (CLAD) estimator. CLAD and STLS estimators are both robust to heteroscedasticity of unknown form. The STLS estimator is more sensitive than the CLAD estimator to outliers but is more efficient. Both censored income functions are modeled as a type I Tobit model, and therefore the selection process is modeled implicitly as being determined by the same variables that explain income. (See the appendix for more details on these estimators.)

Reduced-Form Results

Table 4 summarizes the results from estimating the three reduced-form income functions—total income, farm income, and off-farm income—with OLS, CLAD, STLS, and least absolute deviations (LAD) estimators. Table 4 also summarizes the *F*-statistics, which test the joint significance of the test scores.[2] The primary result from estimating the impact of cognitive skills in the total income function is that the test scores are jointly significant whether the average value or maximum value of test scores is used and whether estimated by OLS or LAD. The weakest case is the LAD estimation using the maximum test scores. In this case, the *F*-statistic for the test of joint significance is 7.96, and the *p*-value is 0.0004.[3]

Each reduced-form function is estimated separately using the household average and maximum test scores. For the sake of brevity, table 5 presents the full estimation results only for the model using the average test scores and the least squares estimators. The estimation results from using the maximum test scores, and the absolute-deviations estimators are qualitatively very similar and are presented in full in Jolliffe (1996). To get a sense of the magnitude of the effect that test scores have on total income, consider the example of increasing both household average scores by one standard deviation. An increase of this size means 7.6 more correct answers on the mathematics test and 9.5 more on the English test. From the results in table 5, this change in test scores results in an increase in total income of 9.6 percent. Repeating this exercise using maximum test scores and the LAD estimates, which are the lowest estimated returns to skills, results in an increase in total income of 6.2 percent. Increasing test scores by one standard deviation is a large change, yet the corresponding effect on total income is significantly smaller than would be expected from the wage studies reviewed in Psacharopoulos (1985 and 1994).

In contrast to the total income estimates, the test scores do not appear to be important determinants of farm income. The hypothesis that jointly the test scores add nothing to the predictive power of the farm income model cannot be

2. The reported *F*-statistics result from Wald tests using robust estimates of the variance-covariance matrix. *F*-tests based on the sum of squares (or *R*-squared) are incorrect when homoscedasticity is violated. The Wald test is robust to heteroscedasticity.

3. The *F*-statistics for the joint significance of the (Huber-corrected) OLS estimates are 14.1 when using the maximum test scores and 11.6 when using the average test scores. Similarly, the *F*-statistic for the joint significance of the LAD estimates is 8.4 when using the average test scores. For all of these statistics, the probability of observing a statistic this large when the null hypothesis is true is essentially 0.

Table 4. *Summary of the Effect of Test Scores on Income, Ghana, 1988–89*

Estimator and variable	*Total income*	*Farm income*	*Off-farm income*
Parameter estimates			
OLS and STLS			
Household maximum English score	0.001	0.012	0.015
	(0.0018)	(0.0081)	(0.0173)
Household maximum mathematics score	0.009***	–0.002	0.049**
	(0.0027)	(0.0104)	(0.0214)
Household average English score	0.003	0.007	0.000
	(0.0028)	(0.0112)	(0.0242)
Household average mathematics score	0.009**	0.000	0.086***
	(0.0043)	(0.0146)	(0.0309)
LAD and CLAD			
Household maximum English score	0.001	0.018	0.060***
	(0.0028)	(0.0174)	(0.0230)
Household maximum mathematics score	0.005	–0.010	0.008
	(0.0034)	(0.0223)	(0.0269)
Household average English score	0.003	0.014	0.055
	(0.0041)	(0.0255)	(0.0344)
Household average mathematics score	0.007	–0.005	0.032
	(0.0049)	(0.0313)	(0.0405)
F-statistics (joint significance of test scores)			
OLS and STLS			
Household maximum score	14.10	2.33	13.88
	[0.0000]	[0.0973]	[0.0000]
Household average score	11.60	0.57	13.43
	[0.0000]	[0.5656]	[0.0000]
LAD and CLAD			
Household maximum score	7.96	0.79	15.3
	[0.0004]	[0.4544]	[0.0000]
Household average score	8.36	0.29	11.35
	[0.0002]	[0.7505]	[0.0002]

Note: The total income functions are estimated by ordinary least squares (OLS) and least absolute deviations (LAD). All measures of income are in logs, and the test scores are in levels. The OLS standard errors are Huber-corrected for heteroscedasticity. The LAD standard errors are bootstrap estimates. The farm and off-farm income functions are estimated by symmetrically trimmed least squares (STLS) and censored least absolute deviations (CLAD). The standard errors are bootstrap estimates. All bootstrap estimates result from resampling 1,000 times. The *F*-statistics are from Wald tests for the joint significance of the mathematics and English test scores. The probability values of the *F*-statistics are reported in square brackets. The degrees of freedom for these statistics and tests of joint significance of other variables are reported in Jolliffe (1996). Standard errors are in parentheses.

**p-value is less than 0.05.

***p-value is less than 0.01.

Source: Author's calculations.

rejected for any of the specifications. This is the case whether the average values or maximum values of the test scores are used and whether estimated by STLS or CLAD. The test scores approach statistical significance only in the case of STLS estimation using maximum test scores. In this case the *F*-statistic for the test of joint significance is 2.3, and the p-value is 0.097.

Table 5. *Full Estimation Results of the Impact of Household Average Test Scores on Income, Ghana, 1988–89*

Variable	OLS, total income	STLS Farm income	STLS Off-farm income
Household average English score	0.003	0.007	0.000
	(0.0028)	(0.0112)	(0.0242)
Household average mathematics score	0.009**	0.000	0.086***
	(0.0043)	(0.0146)	(0.0309)
Log acres of land farmed	0.026*	2.614***	–0.015
	(0.0151)	(0.0417)	(0.0904)
Household average log of farm experience	–0.026	0.624***	–0.925***
	(0.0197)	(0.0639)	(0.1414)
Cluster/zone average day farm wage	0.004	0.139**	–0.086
	(0.0165)	(0.0699)	(0.1476)
Regional average			
Log (price fertilizer)	–0.707***	–1.086**	–0.035
	(0.1448)	(0.5127)	(1.0736)
Log (price insecticide)	–0.032	0.847***	0.422
	(0.1054)	(0.2986)	(0.6162)
Price of maize	0.003***	0.002	0.009
	(0.0009)	(0.0027)	(0.0058)
Price of okra	0.006	–0.000	–0.031
	(0.0045)	(0.0180)	(0.0404)
Price of cassava	–0.004	–0.005	0.022
	(0.0031)	(0.0084)	(0.0178)
Price of pepper	0.001	0.010*	0.004
	(0.0016)	(0.0056)	(0.0129)
Log business assets	0.013***	0.000	0.169***
	(0.0042)	(0.0134)	(0.0272)
Household maximum log (off-farm experience)	0.015	–0.165***	1.993***
	(0.0176)	(0.0508)	(0.1126)
Area average off-farm wage[a]			
Type 1	3.526**	5.582	3.877
	(1.4029)	(6.5144)	(12.942)
Type 2	–0.748**	–0.435	0.177
	(0.3704)	(1.7914)	(3.4869)
Type 3	–1.386***	–1.388	–0.500
	(0.5169)	(2.4705)	(4.8600)
Type 4	–0.607***	–0.706	–0.125
	(0.2079)	(0.8647)	(1.7211)
Type 5	–0.011	–0.613***	–0.426
	(0.0529)	(0.1336)	(0.2756)
Log of household size	0.323***	0.009	–0.428*
	(0.0326)	(0.1124)	(0.2513)
Household gender composition[b]	–0.044	0.259	0.155
	(0.0707)	(0.2463)	(0.5068)
Number of males			
15–24 years old	0.010	–0.132	0.082
	(0.0272)	(0.0902)	(0.1931)

(Table continues on the following page.)

Table 5. *(continued)*

Variable	OLS, total income	STLS Farm income	STLS Off-farm income
25–34 years old	0.146***	–0.117	1.171***
	(0.0375)	(0.1332)	(0.2891)
35–44 years old	0.208***	–0.203	0.310
	(0.0379)	(0.1547)	(0.3374)
45–55 years old	0.146***	–0.275*	0.769**
	(0.0402)	(0.1658)	(0.3635)
Number of females			
15–24 years old	0.102***	0.099	0.518***
	(0.0276)	(0.0928)	(0.1947)
25–34 years old	0.060	0.160	1.181***
	(0.0409)	(0.1340)	(0.2904)
35–44 years old	0.047	0.378**	0.776**
	(0.0407)	(0.1632)	(0.3373)
45–55 years old	0.112***	0.075	–0.572*
	(0.0357)	(0.1490)	(0.3341)
Intercept	17.887***	2.542	0.559
	(1.3403)	(4.9031)	(10.508)
Adjusted R^2	0.35	0.89	0.40
Number of observations	1,388	1,304	1,380

Note: The total income estimates are ordinary least squares (OLS), and the standard errors are Huber-corrected for heteroscedasticity. The farm and off-farm estimates are symmetricallly trimmed least squares (STLS), and the standard errors are bootstrapped. The bootstrapped estimates are generated by resampling the data 1,000 times. The bootstrapping procedure follows the classical assumptions that the independent variables are fixed, and it is the residuals that are resampled. The decision to include some of the variables in log form and the others in levels was made on the basis of goodness of fit and variable significance. Standard errors are in parentheses.

* *p*-value is less than 0.1.

** *p*-value is less than 0.05.

*** *p*-value is less than 0.01.

a. The off-farm wages are regional averages of wages grouped into five occupational types. Type 1 occupations are the lowest-wage activities, and type 5 are the highest. The data on wages come from the half of the sample that was not administered the supplemental education module.

b. Household gender composition is the household average value of the binary variable that takes the value of 1 for men and 2 for women.

Source: Author's calculations.

The results from estimating the impact of cognitive skills in the off-farm income functions are similar to the results from estimating total income. Namely, the test scores are jointly significant across all four specifications. Even the least-significant *F*-statistic strongly rejects the null hypothesis that test scores have no effect.

Two-Stage Results

Up to this point no attempt has been made to determine whether the reduced-form estimates result from changes in farm and off-farm productivity or from changes in labor supply to these two activities. The positive effect of test scores

on off-farm income found in the reduced-form estimates could well be the result of increased productivity or increased effort in off-farm income activities (or both). Similarly the result that no returns are found in farm income could reflect off-setting productivity and labor supply effects. For example, increased test scores might improve farm productivity while decreasing labor supply to farm activities.

To address this issue, farm and off-farm income are also estimated with labor supply explicitly included in the model and treated as an endogenous variable. For the two-stage model of farm profit, the sample is restricted to include only those households engaged in farming. Similarly, the off-farm income model with off-farm labor supply instrumented is also conditioned on the household engaging in off-farm activities. The farm labor supply function is instrumented using the determinants of off-farm income and the log of household size, while the off-farm labor supply function is instrumented by the determinants of farm income and the log of household size. The age and gender household composition variables are used in both stages and can thereby affect income directly and indirectly through labor supply.[4]

It could be argued that the only valid variable to exclude from the second stage of estimation is household size. I do not follow this strategy both because the model implied by this argument is not identified and because there are other valid identifying instruments.[5] For example, increases in off-farm wages may lead households to supply more labor to off-farm activities and thereby decrease farm income, but there is no compelling reason why off-farm wages directly affect farm income.

Table 6 presents the results from these models. The estimates suggest that improved test scores have no joint effect on farm productivity and a positive effect on off-farm productivity. This provides evidence that the estimates from the unconditional, reduced-form off-farm model are due in part to increased productivity from improved cognitive skills. While the two-stage results for the off-farm function show that skills have a positive effect on off-farm income, the parameter estimates are about half the size of the unconditional estimates. This suggests that skills also increase income through either increased effort or an allocative effect. This result is similar to that of Yang (1997), who examines a sample of Chinese farm households and finds that schooling increases off-farm wages. He then argues that better-educated farm households allocate labor in response to increases in off-farm wages.

4. The farm and off-farm income models are also estimated with a set of the excluded variables included. The *F*-tests from these models fail to reject the null hypothesis that the excluded variables are jointly equal to 0. This implies that the over-identifying exclusion restrictions implied by the two-stage least squares model are valid. Similarly, *F*-tests of the joint significance of the excluded variables in the first-stage regression reject the null hypothesis that the excluded variables are jointly 0 in the determination of labor supply. This implies that the excluded variables are jointly significant determinants of farm and off-farm labor supply.

5. It is feasible to estimate this model for the farm income function, but not for the off-farm income function. Household size alone is not sufficient to identify off-farm labor supply.

Table 6. *Impact of Household Average Test Scores on Farm and Off-Farm Income Using Two-Stage Least Squares, Ghana, 1988–89*

Variable	*Farm income*	*Off-farm income*
Household average English score	–0.011	0.013
	(0.0075)	(0.0106)
Household average mathematics score	0.019**	0.032**
	(0.0096)	(0.0128)
Log household farm labor[a]	0.357***	
	(0.1357)	
Log acres of land farmed	0.526***	
	(0.0670)	
Household average log of farm experience	0.175***	
	(0.0612)	
Cluster/zone average day farm wage	–0.022	
	(0.0442)	
Regional average		
Log (price fertilizer)	–0.225	
	(0.3160)	
Log (price insecticide)	–0.171	
	(0.1396)	
Price of maize	0.004	
	(0.0026)	
Price of okra	0.001	
	(0.0133)	
Price of cassava	0.008	
	(0.0088)	
Price of pepper	0.006	
	(0.0048)	
Log household off-farm labor[b]		0.916***
		(0.1916)
Log business assets		0.031**
		(0.0134)
Household maximum log (off-farm experience)		0.042
		(0.1063)
Area average off-farm wage[c]		
Type 1		0.929
		(2.2796)
Type 2		0.155
		(0.7379)
Type 3		0.464
		(0.9787)
Type 4		0.422
		(0.3825)
Type 5		–0.041
		(0.1031)
Household gender composition[d]	0.357**	–0.072
	(0.1635)	(0.2290)
Number of males		
15–24 years old	–0.001	–0.076
	(0.0590)	(0.0922)

Table 6. *(continued)*

Variable	*Farm income*	*Off-farm income*
25–34 years old	0.100	0.144
	(0.0885)	(0.1328)
35–44 years old	0.096	–0.088
	(0.0908)	(0.1552)
45–55 years old	–0.079	0.122
	(0.0965)	(0.1754)
Number of females		
15–24 years old	0.102**	0.097
	(0.0500)	(0.0879)
25–34 years old	0.038	0.170
	(0.0754)	(0.1088)
35–44 years old	0.009	–0.009
	(0.0957)	(0.1475)
45–55 years old	0.000	–0.363**
	(0.0863)	(0.1733)
Intercept	8.266***	2.807***
	(2.5532)	(0.8258)
Adjusted R^2	0.46	0.33
Number of observations	836	962

Note: The farm and off-farm parameter estimates are from two-stage least squares estimation with household labor instrumented. The standard errors are Huber-corrected, and household labor supply is treated as endogenous. The information on household age and gender composition is included in both stages because these characteristics may well affect productivity and thus income independently of their effect on labor supply. Only those households who generated positive farm income are included in the farm regression and similarly only those households with positive off-farm income are included in the off-farm regression. The decision to include some of the variables in log form and the others in levels was made on the basis of goodness of fit and variable significance. The standard errors are in parentheses. Standard errors are Huber-corrected for design effects. See Over, Jolliffe, and Foster (1996) for details.

**p-value is less than 0.05.

***p-value is less than 0.01.

a. Household size and the off-farm variables are used to instrument household farm labor supply.

b. Household size and the farm variables are used to instrument off-farm labor supply.

c. The off-farm wages are regional averages of wages grouped into five occupational types. Type 1 occupations are the lowest-wage activities, and type 5 are the highest. The data on wages come from the half of the sample that was not administered the supplemental education module.

d. Household gender composition is the household average value of the binary variable that takes the value of 1 for men and 2 for women.

Source: Author's calculations.

The reduced-form results presented in tables 4 and 5 differ from the two-stage results presented in table 6 for the model of farm profit. Although the two-stage least squares (2SLS) estimates of the farm profit model fail to reject the null hypothesis that the test scores jointly have no effect on farm profit, they do reject the null hypothesis that the mathematics score is not a significant determinant of farm profit. Conditional on selecting into farming activities, then, improved mathematics scores do seem to improve farm productivity.

The section on reduced-form estimation emphasized the results from the joint tests of significance. This is partly because using semiparametric estimators and

robust estimates of the variance-covariance matrix results in inefficient estimates of the standard errors. Joint tests were necessary to draw any conclusions. The decision to present joint test results is also due to the high level of collinearity between the English and mathematics test scores and a suspicion that the data may not easily allow the English and mathematics effects to be disentangled.

III. Conclusions

The argument for using test scores in lieu of years of schooling to measure human capital is that years of schooling fail to capture any effect that school quality may have on the creation of human capital. This article shows that school quality does vary over Ghana and that the test scores reflect this variation. It also shows that the returns to skills, as measured in the total income models, are positive and significant. This result supplements the human capital literature because it makes clear that skills are rewarded and it provides evidence against the screening and credentialism theories of the returns to schooling.

By estimating total income and its components, rather than focusing on just one source of income such as wage or farm income, the analysis makes statements both about the overall benefits of cognitive skills to households in Ghana and about the sources of income that are most affected by skills. This contrasts with the literature that focuses on specific types of workers in the economy (such as farmers or wage earners), so that the conclusions drawn are applicable only to workers in the same sector. The advantage of broader statements about the benefits accrued from skills is that they provide the policymaker with a clearer picture of the expected results from national education policies.

The results presented here show that the returns to cognitive skills, as found in the total income estimates, are positive and statistically significant. Tests of the robustness of these results, using different household-level measures of skills and different estimation techniques, find that they are robust to the different measures of skills and over a wide class of non-normal error distributions.

The decision to not select either farmers, wage earners, or self-employed family enterprises means that the analysis avoids explicitly modeling the sample selection process but must handle the resulting problem of numerous zero values when estimating farm and off-farm income. (All households that do not farm will have no farm income, and similarly all households that only farm will have no off-farm income.) The presence of sample-selection bias or censored dependent variables is a problem faced by most of the work discussed in the literature, but most of the papers address these problems by assuming that the underlying residuals are normally distributed. Yet, it is well known that the standard maximum-likelihood estimators for the censored model and for correcting sample-selection bias are inconsistent in the presence of heteroscedasticity as well as many other violations of normality (see Vijverberg 1987). It is now more widely acknowledged that most cross-sectional surveys are based on some sort of two-stage sample design, which typically means that the assumption of homo-

scedasticity is not tenable. For these reasons, this article uses Powell's CLAD and STLS estimators, which are robust to heteroscedasticity, for the estimation of farm and off-farm income.

The estimates of farm and off-farm income suggest that none of the returns to skills is found in farm income and that only the off-farm income estimates provide evidence of positive (and statistically significant) returns to skills. This result is robust to the different measures of skills and over a wide class of nonnormal error distributions. This result is somewhat tempered by noting that while the advantage of the STLS and CLAD estimators is their robustness to violations of normality, their disadvantage is a loss of efficiency. Over most of the specifications for farm income, the returns to skills are positive but not significant. It is also tempered by noting the two-stage result that, conditional on selecting to engage in farm work, higher mathematics skills do seem to improve farm productivity.

As a final comment, although the benefits of cognitive skills to Ghanaian households are not found in their effects on farm income, this does not mean that households engaged in farming do not benefit from improved cognitive skills. The GLSS data make clear that the typical household is engaged in numerous income-generating activities. Although a household's farm profitability might not improve, its total income will increase from the improved skills of household members.

Appendix. The Estimators

This article uses two estimators, both of which are consistent and asymptotically normal for a wide class of symmetric error distributions with heteroscedasticity of unknown form and a censored dependent variable. The first is Powell's (1986) symmetrically trimmed least squares (STLS) estimator. The second is Powell's (1984) censored least absolute deviations (CLAD) estimator. The STLS estimator is the β which minimizes:

$$I(x_i'\beta > 0)\,[\min(y_i, 2x_i\beta) - x_i'\beta]^2 \tag{A-1}$$

where y_i is the dependent variable, x_i is the explanatory variable, and the indicator function, I, takes the value of 1 if the argument is true and 0 otherwise. This estimator is obtained by trimming the dependent variable and results in residuals that are distributed over $(-x_i\beta, x_i\beta)$.

The CLAD estimator is the β which minimizes:

$$\Sigma \mid y_i - \max(0, x_i'\beta) \mid. \tag{A-2}$$

The consistency of this estimator rests on the fact that medians are preserved by monotone transformations of the data, and equation A-2 is a monotone transformation of the standard median regression that minimizes the absolute deviations. Koenker and Bassett (1978) discuss the properties of the median regression or the least absolute deviations (LAD) estimator.

The method of estimation used in this article for the CLAD estimator is Buchinsky's (1994) iterative linear programming algorithm (ILPA). The ILPA estimates a quantile regression for the full sample, then deletes the observations for which the predicted value of the dependent variable is less than 0. Another quantile regression is estimated on the new sample, and again negative predicted values are dropped. Buchinsky (1991) shows that if the process converges, then a local minimum is obtained. Convergence occurs when there are no negative predicted values in two consecutive iterations. All of the models estimated here converged, typically in fewer than 15 iterations.

The STLS estimator used in this article is found by an iterative procedure similar to the one used for the CLAD estimator. The first step to finding the STLS estimator is to use OLS estimates on the full sample. A new sample is created by dropping observations with negative predicted values and reassigning values to the dependent variable if it is larger than two times its predicted value. Another OLS regression is estimated on the new sample, and the process of trimming and reassigning values continues until convergence.

The standard errors for the CLAD, STLS, and LAD estimators are bootstrapped by resampling the data 1,000 times. This bootstrap procedure results in standard errors that are robust to violations of the assumption that the residuals are identically distributed. Breusch and Pagan's (1979) test statistics suggest that assuming identically distributed residuals is untenable and the standard errors need to be robust to violations of homoscedasticity. Similarly, the two-stage design of the sample is likely to result in rejection of the assumption that the residuals are independently distributed. An important caveat in interpreting the CLAD, STLS, and LAD estimates is that the bootstrap standard errors are not robust to violations of the independence assumption. This contrasts with the OLS Huber-corrected standard errors, which are robust to violations of both identically and independently distributed residuals. Jolliffe (1996) discusses a general bootstrap method for estimating standard errors that are robust to violations of the assumption of independently distributed residuals.

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