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Oasis, Kodila-Tedika

Department of Economics University of Kinshasa

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Do Nations Combine O-Rings with Cobb-Douglas? Evidence from agriculture, equipment production, and the informal sector

Oasis Kodila-Tedika
Department of Economics
University of Kinshasa, B.P. 832 KIN XI,
Kinshasa, Democratic Republic of Congo.
oasiskodila@yahoo.fr

Abstract

The article focuses on the conditional relationship between various human capital proxies and the size of potential “O-Ring” or “Cobb-Douglas” sectors. We find that that years of schooling are a robust negative predictor of the size of the informal sector, conditioned on national average test scores, suggests that the signaling and acculturation mechanisms of schooling may help shift potentially productive workers into the formal economy.

Keys-words: Intelligence, Human capital; Strategic complementarities

JEL Codes: I2, H11, J24

Introduction

Kremer (1992) posited that much of the output in modern economies is the result of fragile production processes where the payoff to higher average skill is enormous. Jones (2013) noted that if workers of different skill levels could shift endogenously between Kremer's fragile "O-Ring" sector and a traditional Cobb-Douglas sector, intra-country returns to skill might be modest (depending on parameter values) while cross-country returns to average skill would still be massive. In this short note, we test some of the implications of Jones (2013). One implication of the model is that in nations with low levels of average worker skill, workers are more likely to endogenously sort into the Cobb-Douglas style sectors where there are no strategic complementarities to worker skill. In practice, these sectors may include the informal sector and traditional agriculture, where differences in worker training have modest impacts on productivity. Conversely, the manufacture of globally competitive manufactured equipment may be an O-Ring process, characterized by strategic complementarities to worker skill, where one error in the production process can destroy the value of the product. As Hsieh and Klenow note, "Poor countries...appear to be plagued by low efficiency in producing investment goods..." (2007, p562), and Eaton and Kortum (2002, p.1195) note, "Innovative activity is highly concentrated in a handful of advanced countries. These same countries are also the major exporters of capital goods to the rest of the world."

Of course, higher levels of average human capital are positively correlated with larger formal sectors, smaller fractions of the population working in agriculture, and greater levels of equipment production, but this may largely be a result of reverse causation (Bils and Klenow, 2000). In addition, a key question of interest is *which* indices of human capital might be most valuable for potentially moving into O-Ring style production: Years of education or standardized test scores? The former may capture the acculturation aspects of education or may provide useful signals to potential employers, while the latter may encompass effective teaching methods as well as healthier environments (Eppig et al. 2010). We use cross-country data on education, test scores, and the size of different economic sectors, and find only limited evidence that national average scores are an important drivers of outcomes.

Data

Outcomes. Agriculture value added (% of GDP), Employment in agriculture (% of the total of employment) and Industry value added (% of GDP) are obtained from the World

Development Indicators of the World Bank. Equipment production (% of GDP) comes from Eaton and Kortum (2002). Persons employed in the informal sector are obtained from the statistical update on employment in the informal economy, ILO department of statistics (June -2011).

Human capital indices. Intelligence quotient scores have been estimated by Lynn et al., (2002, 2006 and 2010); Wicherts et al. (2009, 2010a,b). provide evidence that sub-Saharan African IQ scores in the Lynn/Vanhanen database are inaccurately low; when Wicherts et al. reestimate using healthy samples of typical SES, they find higher average IQ scores in this region of the world. We therefore run additional estimates where the minimum national average IQ in sub-Saharan Africa is 76 (Wicherts et al. 2010a) and 80 (Wicherts et al. 2010b)¹. Cognitive ability mean scores, based on PISA and TIMSS international standardized test scores, come from Rindermann, Sailer and Thompson (2009). These data have recently been used in Kodila-Tedika (2013). Average years of schooling are from Barro and Lee (2010) for 2005.

Additional Controls. As control variables, we include the log of GDP per capita (from Penn World Tables 6.3) for 2005; legal origin and geographical location (all as dummy variables). Following the trend in the literature, legal origin is captured by distinguishing between the English, French, German, Scandinavian and socialist legal heritages. The Legal Origin dummy variables are taken from La Porta et al. (1999). The five geographic locations are: Africa, the Americas, Asia, Europe, Oceania (the omitted dummy). Government Effectiveness (year 2005) is the measures of institutional quality come from the dataset compile by Daniel Kaufmann, and Art Kraay and Massimo Mastruzzi at the World Bank. The aggregate indicators are based on 30 underlying data sources reporting the perceptions of governance of a large number of survey respondents and expert assessments worldwide.

Estimation results and conclusion

We estimate using OLS with robust standard errors, and in addition use iteratively weighted least squares (IWLS) procedure to mitigate the influence of outlier observations. Average years of schooling are a robust predictor of the share of employment in agriculture across all specifications in Tables 1, 2, and 3, easily more robust than IQ or mean cognitive ability. Due to the small sample size for the informal sector regressions, we run an additional specification

¹ This indicator was also heavily used recently (Lynn and Vanhanen, 2012; Kodila-Tedika, 2012; Kodila-Tedika, 2013; Kalonda-Kanyama and Kodila-Tedika, 2012).

that includes interpolated values for national average IQ; these interpolated values were used by Eppig et al. (2010) to demonstrate that infectious disease levels within a country are a robust predictor of national average IQ. Here we find additional evidence that higher years of schooling predict a smaller informal sector across all IQ-based specifications, whether or not one controls for log GDP per capita and other factors.

There is more fragile evidence that average IQ and cognitive ability predict rates of equipment production as a percent of GDP: these test scores are statistically significant and quantitatively large in the IWLS specifications but less significant in the OLS specifications. Interpreting our estimates causally, one would predict that each additional year of schooling would shrink agricultural employment by perhaps 1 to 3 percent of the labor force, while raising IQ by 10 points via health, nutritional and educational quality interventions would raise the equipment share of output by 1.7 to 3 percent of GDP.

These are the first results reporting the conditional relationship between various human capital proxies and the size of potential “O-Ring” or “Cobb-Douglas” sectors. Future work can investigate potential causal mechanisms and search for improved instruments for human capital. But the finding that years of schooling are a robust negative predictor of the size of the informal sector, conditioned on national average test scores, suggests that the signaling and acculturation mechanisms of schooling may help shift potentially productive workers into the formal economy.

Annexes

Table 1. Main result

Persons employed in the informal sector						
IQ 2010	-.1077 (0.895)	.072 (0.867)	-.036 (0.967)	.0494 (0.913)	-.036 (0.967)	-.051 (0.962)
School	-4.919 (0.195)	1.552 (0.378)	-4.995 (0.196)	1.362 (0.454)	-4.995 (0.196)	-3.993 (0.353)
Obs	16	16	16	15	16	14
R-squared	0.76		0.76		0.76	
Method	OLS	IWLS	OLS(Minimum IQ for African countries: 80)	IWLS (Minimum IQ for African countries: 80)	OLS(Minimum IQ for African countries: 76)	IWLS (Minimum IQ for African countries: 76)
Agriculture value added (% of GDP)						
IQ	-.358 (0.016)	-.382 (0.000)	-.282 (0.193)	-.231 (0.064)	-.316 (0.112)	-.295 (0.020)
School	-1.927 (0.000)	-.534 (0.062)	-2.111 (0.000)	-.742 (0.022)	-2.076 (0.000)	-.753 (0.028)
Obs	63	63	63	63	63	63
R-squared	0.64		0.62		0.63	
Method	OLS	IWLS	OLS(Minimum IQ for African countries: 80)	IWLS (Minimum IQ for African countries: 80)	OLS(Minimum IQ for African countries: 76)	IWLS (Minimum IQ for African countries: 76)
Employment in agriculture (% of the total of employment)						
IQ	-.624 (0.226)	-.651 (0.000)	-.624 (0.226)	-.651 (0.000)	-.624 (0.226)	-.651 (0.000)
School	-3.167 (0.015)	-1.352 (0.002)	-3.167 (0.015)	-1.352 (0.002)	-3.167 (0.015)	-1.352 (0.002)
Obs	36	36	36	36	36	36
R-squared	0.72		0.72		0.72	
Method	OLS	IWLS	OLS(Minimum IQ for African countries: 80)	IWLS (Minimum IQ for African countries: 80)	OLS(Minimum IQ for African countries: 76)	IWLS (Minimum IQ for African countries: 76)
Industry value added (% of GDP)						
IQ	-.214 (0.557)	.216 (0.308)	-.6794 (0.186)	-.163 (0.543)	-.540 (0.249)	-.044 (0.862)
School	-.618 (0.436)	-.810 (0.230)	-.255 (0.751)	-.4207 (0.540)	-.379 (0.636)	-.523 (0.443)
Obs	64	64	64	64	64	64
R-squared	0.15		0.20		0.18	
Method	OLS	IWLS	OLS(Minimum IQ for African countries: 80)	IWLS (Minimum IQ for African countries: 80)	OLS(Minimum IQ for African countries: 76)	IWLS (Minimum IQ for African countries: 76)
Equipment production (% of GDP)						
IQ	.207 (0.026)	.261 (0.000)	.230 (0.085)	.396 (0.000)	.243 (0.050)	.396 (0.000)
School	.303 (0.193)	.170 (0.285)	.183 (0.404)	.082 (0.633)	.207 (0.324)	.170 (0.229)
Obs	30	29	30	29	30	30
R-squared	0.85		0.84		0.85	
Method	OLS	IWLS	OLS(Minimum IQ for African countries: 80)	IWLS (Minimum IQ for African countries: 80)	OLS(Minimum IQ for African countries: 76)	IWLS (Minimum IQ for African countries: 76)

	countries: 80)		countries: 80)		countries: 76)		countries: 76)	
Persons employed in the informal sector								
IQ 2006	-1.184 (0.018)	-.939 (0.107)	-1.132 (0.077)	-.468 (0.465)	-1.262 (0.048)	-.795 (0.247)		
School	-4.691 (0.004)	-5.627 (0.002)	-5.267 (0.003)	-5.070 (0.002)	-4.932 (0.004)	-5.766 (0.002)		
Obs	33	33	33	33	33	33		
R-squared	0.69		0.67		0.68			
Method	OLS	IWLS	OLS(Minimum IQ for African countries: 80)	IWLS (Minimum IQ for African countries: 80)	OLS(Minimum IQ for African countries: 76)	IWLS (Minimum IQ for African countries: 76)		
Equipment production (% of GDP)								
IQ	-.081 (0.907)	-1.738 (0.000)	2.122 (0.237)	.667 (0.717)	2.118 (0.095)	2.046 (0.000)		
School	-.123 (0.897)	.686 (0.121)	-.304 (0.757)	.744 (0.240)	-.153 (0.871)	1.577 (0.000)		
IQ*IQ	.002 (0.701)	.012 (0.000)	-.010 (0.298)	-.001 (0.886)	-.010 (0.156)	-.009 (0.000)		
School *	.027 (0.730)	-.046 (0.107)	.036 (0.649)	-.049 (0.236)	.0311 (0.689)	-.0926 (0.000)		
Obs	30	30	30	30	30	29		
R-squared	0.85		0.85		0.864			
Method	OLS	IWLS	OLS(Minimum IQ for African countries: 80)	IWLS (Minimum IQ for African countries: 80)	OLS(Minimum IQ for African countries: 76)	IWLS (Minimum IQ for African countries: 76)		

All regressions are estimated using White (1980) heteroskedasticity correction except for IWLS. All regressions include regional dummies Legal Origin dummy (French, German, Scandinavian, Socialist and British) and constant. P-values are in parentheses.

Table 2. Additional control variables (Gdp per capita (log) and government effectiveness included)

Persons employed in the informal sector							
IQ 2010	-.6708 (0.296)	not converge	-.6036 (0.355)	not converge	-.6036 (0.355)	not converge	
School	.97096 (0.774)		1.0161 (0.766)		1.0161 (0.766)		
Obs	15		15		15		
R-squared	0.89		0.89		0.89		
Method	OLS	IWLS	OLS(Minimum IQ for African countries: 80)	IWLS (Minimum IQ for African countries: 80)	OLS(Minimum IQ for African countries: 76)	IWLS (Minimum IQ for African countries: 76)	
Agriculture value added (% of GDP)							
IQ	-.01085 (0.940)	.09897 (0.331)	.1377 (0.346)	.127 (0.314)	.124 (0.407)	.1577 (0.194)	
School	-.6084 (0.260)	-.2719 (0.447)	-.6419 (0.249)	-.381 (0.300)	-.623 (0.264)	-.3709 (0.308)	
Obs	61	61	61	61	61	61	
R-squared	0.82		0.83		0.83		
Method	OLS	IWLS	OLS(Minimum IQ for African countries: 80)	IWLS (Minimum IQ for African countries: 80)	OLS(Minimum IQ for African countries: 76)	IWLS (Minimum IQ for African countries: 76)	
Employment in agriculture (% of the total of employment)							

IQ	-0.3048 (0.552)	-0.8355 (0.001)	-0.304 (0.552)	-0.8355 (0.001)	-0.3048 (0.552)	-0.8355 (0.001)
School	-2.6685 (0.047)	-1.391 (0.000)	-2.668 (0.047)	-1.391 (0.000)	-2.6685 (0.047)	-1.391 (0.000)
Obs	36	36	36	36	36	36
R-squared	0.75		0.74		0.74	
Method	OLS	IWLS	OLS(Minimum IQ for African countries: 80)	IWLS (Minimum IQ for African countries: 80)	OLS(Minimum IQ for African countries: 76)	IWLS (Minimum IQ for African countries: 76)
Industry value added (% of GDP)						
IQ	-0.0439 (0.854)	-0.0199 (0.930)	-0.30462 (0.243)	-0.336 (0.234)	-0.245 (0.358)	-0.2765 (0.312)
School	-0.9139 (0.147)	-0.9578 (0.229)	-0.8476 (0.190)	-0.8901 (0.274)	-0.8946 (0.164)	-0.935 (0.252)
Obs	62	62	62	62	62	62
R-squared	0.44		0.45		0.19	
Method	OLS	IWLS	OLS(Minimum IQ for African countries: 80)	IWLS (Minimum IQ for African countries: 80)	OLS(Minimum IQ for African countries: 76)	IWLS (Minimum IQ for African countries: 76)
Equipment production (% of GDP)						
IQ	.171 (0.095)	.271 (0.001)	.190 (0.139)	.304 (0.000)	.201 (0.108)	.354 (0.000)
School	.285 (0.259)	.043 (0.778)	.176 (0.446)	.020 (0.899)	.201 (0.373)	.191 (0.135)
Obs	30	29	30	28	30	30
R-squared	0.85		0.86		0.862	
Method	OLS	IWLS	OLS(Minimum IQ for African countries: 80)	IWLS (Minimum IQ for African countries: 80)	OLS(Minimum IQ for African countries: 76)	IWLS (Minimum IQ for African countries: 76)
Persons employed in the informal sector						
IQ2006	-0.483 (0.376)	-0.5045 (0.519)	-0.390 (0.552)	-0.373 (0.663)	-0.540 (0.397)	-0.534 (0.528)
School	-4.232 (0.006)	-4.646 (0.024)	-4.391 (0.004)	-4.631 (0.019)	-4.249 (0.005)	-4.573 (0.024)
Obs	33	33	33	33	33	33
R-squared	0.74		0.73		0.74	
Method	OLS	IWLS	OLS(Minimum IQ for African countries: 80)	IWLS (Minimum IQ for African countries: 80)	OLS(Minimum IQ for African countries: 76)	IWLS (Minimum IQ for African countries: 76)
Equipment production (% of GDP)						
IQ	- .489(0.6 12)	-1.298 (0.015)	.696 (0.717)	.069 (0.970)	1.490 (0.383)	.754 (0.439)
School	-0.185 (0.849)	.605 (0.239)	-0.346 (0.730)	.537 (0.368)	-0.060 (0.948)	1.048 (0.014)
IQ*IQ	.004 (0.488)	.008 (0.004)	-0.003 (0.802)	.002 (0.879)	-0.007 (0.475)	-0.002 (0.653)
School *	.036 (0.634)	-0.043 (0.172)	.043 (0.591)	-0.036 (0.353)	.032 (0.664)	-0.069 (0.011)
School						
Obs	30		30		30	
R-squared	0.88		0.87		0.88	
Method	OLS	IWLS	OLS(Minimum IQ for African countries: 80)	IWLS (Minimum IQ for African countries: 80)	OLS(Minimum IQ for African countries: 76)	IWLS (Minimum IQ for African countries: 76)

	countries: 80)	countries: 80)	countries: 76)	countries: 76)
All regressions are estimated using White (1980) heteroskedasticity correction except for IWLS.				
All regressions include regional dummies Legal Origin dummy (French, German, Scandinavian, Socialist and British) and constant. P-values are in parentheses.				

Table 3. Regressions with Cognitive ability mean (CA)

Persons employed in the informal sector				
CA	-1.658 (0.002)	-1.541 (0.018)	-2.606 (0.005)	not converge
School	-1.714 (0.680)	-4.340 (0.285)	-3.097 (0.432)	
Obs	14	13	13	
R-squared	0.85		0.91	
Method	OLS	IWLS	OLS (Gdp per capita (log) and government effectiveness included)	IWLS (Gdp per capita (log) and government effectiveness included)
Agriculture value added (% of GDP)				
CA	-.302 (0.245)	-.185 (0.005)	-.164 (0.567)	-.094 (0.285)
School	-2.823 (0.056)	-.917 (0.008)	-.512 (0.479)	-1.067 (0.011)
Obs	59	59	56	56
R-squared	0.20		0.32	
Method	OLS	IWLS	OLS (Gdp per capita (log) and government effectiveness included)	IWLS (Gdp per capita (log) and government effectiveness included)
Employment in agriculture (% of the total of employment)				
CA	-.705 (0.123)	-.252 (0.135)	-.227 (0.582)	-.088 (0.650)
School	-2.001 (0.025)	-2.065 (0.000)	-2.084 (0.026)	-2.368 (0.000)
Obs	38	38	37	37
R-squared	0.62		0.67	
Method	OLS	IWLS	OLS (Gdp per capita (log) and government effectiveness included)	IWLS (Gdp per capita (log) and government effectiveness included)
Industry value added (% of GDP)				
CA	-.1077 (0.750)	.028 (0.864)	.769 (0.039)	.414 (0.050)
School	-.797 (0.579)	.757 (0.381)	1.202 (0.198)	1.050 (0.272)
Obs	60	60	57	56
R-squared	0.12		0.36	
Method	OLS	IWLS	OLS (Gdp per capita (log) and government effectiveness included)	IWLS (Gdp per capita (log) and government effectiveness included)
Equipment production (% of GDP)				
CA	.085 (0.396)	.143 (0.018)	.065 (0.540)	.119 (0.011)
School	.409 (0.372)	.142 (0.564)	.404 (0.421)	.148 (0.367)

Obs	23	22	23	21
R-squared	0.82		0.83	
Method	OLS	IWLS	OLS (Gdp per capita (log) and government effectiveness included)	IWLS (Gdp per capita (log) and government effectiveness included)

All regressions are estimated using White (1980) heteroskedasticity correction except for IWLS. All regressions include regional dummies Legal Origin dummy (French, German, Scandinavian, Socialist and British) and constant. P-values are in parentheses.

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Figure 5

