Technological Change in Africa: Will Ghana turn into South Korea?

Manufacturing firms in Ghana and South Korea use different technologies, by which we mean that the quantitative characteristics of the production function differ. Elements of technological difference, in particular the way in which skills are used in firms, can be shown to account for differences in output per worker. This paper asks whether Ghanaian firms would prefer to use the South Korean technology and how such a switch may occur. We test and ultimately reject the idea that scale and factor proportions lie behind the transition between these technologies. There is a systematic relationship between technology and development. Understanding how and why firms choose and use these different technologies is integral to understanding the development process. This paper shows a potential mechanism through which improved institutions and investment climate can lead to higher living standards.

Simon Baptist[1]
Centre for the Study of African Economies, University of Oxford
This draft: March 2008 (please do not cite without contacting me first)

[1]This paper is not complete so this isn't a formal acknowledgements section yet. In the interim though I would like to recognise the continuing assistance of my co-author and supervisor Francis Teal, the hours of programming time saved thanks to Mans Soderbom kindly giving me some STATA code for the translog regularity tests, the agencies who funded the collection of this data (see later), and the University of Tasmania and the Oxford-Australia Trust for funding. Email simon.baptist@economics.ox.ac.uk.

1 Introduction

African firms are very different from firms in East Asia and, on many measures, they are not as successful. They are, on average, smaller, use different factor proportions, different technology, face different factor prices and have different qualities of inputs (including human capital). In an earlier paper we showed that output per worker differentials between Ghanaian and South Korean firms result from a difference in production technology and a difference in the firm-level returns to worker education. Once these two elements were taken into account it was not possible to identify a significant difference in TFP in firms across the two countries. Thus this paper takes technology and the returns to education in the firm as its focus. Of course firms in Africa are not necessarily homogenous and this paper will investigate how firms differ within the continent and use this information to inform understanding of the cross-country comparison. Institutions and the investment climate have become two important themes of development economics in recent years[Collier, 2007]. This paper shows a potential mechanism through which improved institutions and investment climate can lead to higher living standards, that is, through facilitating technology choice.

Section 2 presents a basic analytical model to give a framework as to why technology may differ across firms and countries. The econometric starting point for the analysis is a 4-factor gross output Cobb-Douglas production function where the output of firm i at time t, Y_{it}, is a function of physical capital K_{it}, human capital $e^{\phi(E_{it})}L_{it}$ (itself a function of average worker years of schooling E and number of workers L), raw material inputs M_{it}, indirect costs O_{it}, total factor productivity α_t and other firm-specific factors X_{it}. The basic specification is thus given as:

$$lnY_{it} = \alpha_t + \beta_K lnK_{it} + \beta_L lnL_{it} + \beta_O lnO_{it} + \beta_M lnM_{it} + \phi(E_{it}) + \delta X_{it}. \quad (1)$$

Initially the function ϕ is taken to be quadratic in E and the vector X consists of firm age, a dummy taking the value 1 if the firm exports, a dummy taking the value 1 if the firm has any foreign ownership, and dummies for the country and sector in which the firm operates. The term ‘technology’ refers to the magnitude of the coefficients β and the function ϕ. If these differ between countries then it is said that firms in the two countries use a different technology. More specifically, if the parameters of ϕ differ then it is said that technology differs in that the way in which they use skills is different. Total factor productivity is given by α and it is allowed to differ over time and also by the variables in the vector X.

Section 3 takes the specification given by equation 1 to answer the question "does technology differ between countries within Africa?" The patterns of technological difference within Africa will be shown to form a coherent narrative with the differences that have been observed between Africa and elsewhere. Section 4 generalises the Cobb-Douglas specification in equation 1 and introduces some dynamics into the production function to allow for a more precise characterisation of the production process, and also in order to ascertain whether technology is truly distinct between countries and if there is an expansion path which will move the characteristics of African firms closer to those in South Korea. Having concluded that technology is indeed distinct and is systematically linked with development the role of education and material use will be considered. Section 5 concludes.

2 Technology Choice

This paper follows on from Baptist and Teal[2008], where technology and the returns to education were shown to differ substantially between Ghana and South Korea and also shown to account for the entire difference in output per worker. It can be seen from Table 1 that the major quantitative differences between the production functions of the two countries are that the material elasticity of output is much higher for Ghana, the labour elasticity much lower, and the rate of return on education is lower and convex. Note that, throughout this paper, the returns to education are taken to refer to the return received by the firm in the form of increased output when the average number of years of schooling of its employees increases.

Why might technology differ? A lot of people might say that it is just through constraint eg patents, financing. But in an increasingly global market for manufactures and the firms that produce them, this argument is more difficult to sustain. This leads to the idea that firms in Ghana are choosing, for whatever reason, to use a different technology to those in South Korea. Is there ever a reason why a firm might choose one technology over another? If the technologies can be unambiguously ranked then no. If one technology produces more output than another for all levels of inputs, then clearly a rational unconstrained firm will always choose to use it. The more interesting case is where technologies cannot be unambiguously ranked, as in the

	Ghana			Korea		
	OLS	FE	GMM	OLS	FE	GMM
lnK	0.035	0.026	0.051	0.110	0.084	0.162
	[0.012]**	[0.010]*	[0.021]*	[0.028]**	[0.025]**	[0.084]
lnH	0.129	0.183	0.133	0.414	0.465	0.347
	[0.014]**	[0.013]**	[0.025]**	[0.037]**	[0.037]**	[0.091]**
lnI	0.184	0.150	0.154	0.225	0.200	0.148
	[0.018]**	[0.010]**	[0.023]**	[0.030]**	[0.025]**	[0.061]*
lnM	0.651	0.641	0.663	0.252	0.251	0.343
	[0.024]**	[0.010]**	[0.027]**	[0.037]**	[0.025]**	[0.077]**
E	-0.094		-0.104	0.475		0.444
	[0.039]*		[0.047]*	[0.253]		[0.241]
E^2	0.006		0.007	-0.014		-0.014
	[0.002]**		[0.003]*	[0.010]		[0.010]
Constant	2.116	1.944	2.114	1.351	5.392	0.946
	[0.217]**	[0.056]**	[0.265]**	[1.575]	[0.242]**	[1.558]
Observations	1880	1880	1880	918	918	918
Firms		254	254		357	357
CRS	0.079	0.000	0.667	0.316	0.000	0.171
Educ	0.009		0.049	0.000		0.000
AR1			0.000			0.482
AR2			0.000			
AR3			0.455			
Sargan			144.21			15.343
Sargan df			145			17
Sargan p			0.503			0.571

Table 1: Production functions in 1996 $PPP for Ghana and South Korea with education included as a quadratic effect. Constant returns to scale in K, L, I and M have been imposed and CRS is the p-value from a Wald test of this hypothesis. Educ is a Wald test of the null hypothesis that both education coefficients are zero. The autocorrelation test for the system GMM estimates cannot reject AR2 for Ghana so we take the 't-3' and 't-4' lags as instruments using the restriction suggested by Bowsher[2001]. AR1 was not rejected for South Korea so all possible lags were used. Year dummies were included but have not been reported. For all pairs of year dummies is is not possible to reject the null that the constant terms are equal across countries.

model of Elberfeld and Götz[2002]. If there are tradeoffs between different elements of technologies then heterogenous choice may exist in equilibrium. Investing in a new technology could be considered akin to capacity choices or investments to reduce marginal costs in a Cournot oligolоply. It follows fairly easily from the Cournot model that some of the key parameters are market power (ie number of competitors and their technological choices), marginal costs and switching costs.

Consider the global production function as the locus enveloping all possible local production function. Jones[2005] puts forward the idea that the standard production function that is written can be viewed, not as a single production function, but rather as a representation of the substitution possibilities across a range of technologies. In a two-factor world, the elasticity of substitution between labour and capital embodied by this global function then depends upon the number of ideas (production techniques) available for producing output at a given capital-labour ratio. He produces simulations to show that, for certain distributions of ideas, that an economy can switch techniques over time. A country will choose a local production technology within the global frontier that equates the ratio of factor shares to the ratio of elasticities of the technology menu. This provides a theoretical basis for the idea that technology can differ across countries and across time. The firm-specific data and prices that are used in this thesis mean that we are observing points along the local production frontier and so may identify different functions.

Caselli and Coleman[2006] empirically investigate a particular type of technological heterogeneity. They differentiate between skilled and unskilled workers and assume they are imperfect substitutes. Although, in the framework used in this paper, they are not allowing for technology to differ, but, rather, allowing for the productivity of skilled and unskilled workers to differ. They find that high-income countries use skilled labour more efficiently and, as an explanation for this, propose that skilled-labour abundant rich countries choose technologies that are best suited to skilled workers. Again, technology is used by them to refer to productivity levels across inputs rather than coefficient differences.

There are also models which explain different outcomes from a single technology. Deardorff[2001] develops a 3-good, 2-factor model in which diverse endowments lead to distinct specialisation cones with a common technology. Despite having the same menu of choices open to them, countries will end up producing differently. Some other macroeconomic models have technological differences as an important element[Grossman and Helpman, 1995], however take differing technologies as exogenous. Exogenous heterogeneity may be the result of uninsurable chance events or differences in ex ante opportunity costs.

Market size may also have an impact through its effects on the cost of adoption. It is well known that the cumulative distribution function of adoptions over time is S-shaped, that is, imitation is initially slow, then accelerates until eventually slowing down as saturation is reached. This suggests that there may be some network externalities in the adoption of new technology and is why we consider technology choice at the country level. Servϑn[1997] has discussed investment under uncertainty and irreversibility in an African context, and this part of the investment literature may be informative if we view technology choice as a form of investment where firms pay a fixed cost ('invest') to switch from the small to the large technology. In this context, the irreversibility could result from imperfect capital markets. Adoption of the large technology in a developing country is possibly deterred by poor resale value of equipment, with the irreversibility decreasing as the penetration of the large technology increases, thus creating the externality. Pack[1993] notes that African markets are not filled with potential entrants to buy physical assets of defunct firms, so when bankruptcy occurs, it generally results in dispersion of skilled workers and loss of productive power of physical equipment, rather than their transfer to a more productive firm. These arguments open up the possibility that African firms may be willingly choosing to use a different technology.

Uncertainty and risk are often cited as reasons for the low levels of investment in African economies[Servϑn, 1997], and uncertainty can lead to firms being less willing to commit to sunk costs[Lambson, 1991]. However, the effect of risk on investment is ambiguous and firms may end up with excess capital stocks in a risky environment[Abel and Eberly, 1999]. Some heterogeneity between Ghana and South Korea is required if endogenous technology choice is to be explained. There is a large literature taking the view that, directly or indirectly, risk and uncertainty are key to understanding the poor performance of African economies[Bleaney, 1996, Servϑn, 1997, Ibarra, 1995]. The idea that risk and business conditions faced by firms differ in Ghana can be used to develop a simple framework which will result in Ghanian firms choosing a 'small' technology (low fixed costs and high variable costs) and South Korean firms choosing a 'large' technology (high fixed costs and low marginal costs).

Theorem 2.1 *Assume that all firms are risk-neutral, maximise discounted expected profits, have a constant discount factor* δ *and are subject to profit shocks* σ *with mean zero and a cumulative density function* $F(\sigma)$. *Further assume that South Korean firms are infinitely lived, but Ghanian firms will cease to exist if they receive a negative shock of magnitude larger than* σ^*. *If a firm uses the small technology there is a mean-preserving transformation of the impact of the shock such that the cumulative density function of the shock changes to* $G(\sigma)$. *Ghanian firms will endogenously choose the small technology if* $G(\sigma*) < F(\sigma*)$.

Proof 1 *Denote normal profits as* Π^0 *and let the shock have a multiplicative effect on profits. The value of* Π^0 *may differ between countries although it need not do so. Define* I_x *as an indicator function taking the value 1 if the event* x *is true, and taking the value 0 otherwise. The value of a South Korean firm using the large technology is given by*

$$\begin{aligned} V_t &= E(\Pi_t) + \delta V_{t+1} && (2) \\ &= \Pi^0 E(\sigma) + \delta V_{t+1} && (3) \\ &= 0. && (4) \end{aligned}$$

The same result attains for South Korean firms using the small technology. Thus, South Korean firms will be indifferent between the two technologies. The value of a Ghanaian firm using the large technology is given by

$$\begin{aligned} V_t &= E(\Pi_t) + \delta V_{t+1} && (5) \\ &= \Pi^0 E(\sigma) + \delta E(I_{\sigma > \sigma^*} V_{t+1}) && (6) \\ &= 0 + \delta(1 - F(\sigma^*))E(V_{t+1}) && (7) \\ &= \delta(1 - F(\sigma^*))\delta(1 - F(\sigma^*))E(V_{t+2}) && (8) \\ &= \Pi_{i=1}^{\infty}[\delta(1 - F(\sigma^*))]. && (9) \end{aligned}$$

For a Ghanian firm using the small technology, the corresponding expression is

$$\begin{aligned} V_t &= E(\Pi_t) + \delta V_{t+1} && (10) \\ &= \Pi_{i=1}^{\infty}[\delta(1 - G(\sigma^*))]. && (11) \end{aligned}$$

Thus a Ghanian firm will choose the small technology if $G(\sigma^*) < F(\sigma^*)$.

Example 2.2 *Let $F(\sigma)$ be uniformly distributed over the interval [-1,1] and $G(\sigma)$ be uniformly distributed over the interval $[-\epsilon,\epsilon]$. Ghanian firms will endogenously choose the small technology if $\epsilon < 1$.*

Proof 2 *The result that South Korean firms are indifferent follows trivially. The value of a Ghanaian firm using the large technology is given by*

$$\begin{aligned} V_t &= E(\Pi_t) + \delta V_{t+1} && (12)\\ &= \Pi^0 E(\sigma) + \delta E(I_{\sigma>\sigma^*} V_{t+1}) && (13)\\ &= 0 + \frac{\delta(1+\sigma^*)}{2} V_{t+1} && (14)\\ &= \frac{\delta(1+\sigma^*)}{2}\frac{\delta(1+\sigma^*)}{2} V_{t+2} && (15)\\ &= \Pi_{i=1}^{\infty}[\frac{\delta(1+\sigma^*)}{2}]. && (16) \end{aligned}$$

For a Ghanian firm using the small technology, the corresponding expression is

$$\begin{aligned} V_t &= E(\Pi_t) + \delta V_{t+1} && (17)\\ &= \Pi_{i=1}^{\infty}[\frac{\delta(\epsilon+\sigma^*)}{2\epsilon}]. && (18) \end{aligned}$$

Thus a Ghanian firm will choose the small technology if

$$\frac{\delta(\epsilon+\sigma^*)}{2\epsilon} > \frac{\delta(1+\sigma^*)}{2} \Leftrightarrow \epsilon < 1. \quad (19)$$

The key differentials required between the firms for this result to hold are that Ghanian firms are more credit constrained and that the small technology somehow insulates the firm from large negative shocks. The idea that manufacturing firms in a developing country face greater credit constraints than those in developed economies has wide empirical and theoretical support in the literature[Bigsten et al., 2003, Habyarimana, 2003].

Many of the assumptions in the model could be relaxed without affecting the fundamentals of the result. Allowing δ to differ between countries has no impact upon the results. Similarly, if the distribution of the shocks is constant over time, a time-varying discount factor will not change the result. Again, because the result hinges upon a within-country choice, the distribution of the shocks could be allowed to vary over time with a time-varying discount rate so long as F and G were transformed in the same way. The distribution of the shock can also differ between countries as long as the transformation is still mean-preserving. If the F and G distributions vary over time and the discount rate is time-varying, then it would not be possible to determine a technology choice condition without specifying how each parameter evolved. The risk-preferences of the firms could also be easily generalised, most simply by using a risk-weighted measure of profit. If a firm is risk-averse then it will place more weight on the probabilities of going bankrupt, and so will be more likely to choose the technology that reduced it's likelihood of ceasing to exist. This can therefore also be modelled as a decrease in the discount factor (an increase in the discount rate).

The idea that only the lower tail of the distribution is important has support in the existing literature. Only downside risk matters in the analysis of investment under uncertainty [Hubbard, 1994, Servϑn, 1997], and a mean-preserving increase in the variance of the payoff from an investment will reduce investment.[2] South Korean firms have zero probability of going bankrupt and so are indifferent between the technologies. If they had a positive probability of going bankrupt given a sufficiently high negative profit shock then *a priori* they, too, would prefer the small technology. To add predictive power to the model in that context, there are two ways that it could be extended. Firstly, the transformation need not be mean-preserving and the insulation provided by the small technology could be made at the expense of a transformation that reduced the mean. Secondly, as the model stands, the distribution of the positive shocks is irrelevant except to the extent of meeting the mean-preserving property. The large technology may require periodic large investments, say to cover depreciation of sophisticated capital equipment, which can only be undertaken in periods of a sufficiently high profit shock. The mean-preserving condition would necessitate that these would be more likely under the large technology. This would also remove any ambiguity from South Korean firms being indifferent between the two technologies.

The $F \to G$ transformation is key. What economic intuition can support the idea that a small technology will provide some insulation from shocks? Consider the following scenario. When a firm using the large technology receives a positive demand shock, it is able to easily expand output and increase profit. However, when it receives a negative demand shock, it cannot reduce

[2] Thus, for example, the stability of macroeconomic variables is as important as their level.

costs optimally due to its capacity commitment and so suffers a period of loss. Conversely, the small technology is able to respond to both shocks, however cannot increase production beyond a relatively low capacity constraint. That is, they cannot gain substantially from any upside, but limit their downside risk. Thus, for a given demand shock distribution, the resultant shocks to firm profit have a lower variance if using the small technology. This distinction between demand-shocks and the resultant profit-shocks by firms, and the channels through which they are transmitted, is the central plank of this hypothesis.

Technology choice can be driven by switching costs and profits differing by technology, partly due to the relative role of variable versus fixed factors in production. We know that technology differs between Ghana and South Korea. In Section 3 we investigate what happens within Africa and try to work out which factors are associated with technology choice.

3 Technology across the Continent

Technology differs between firms in Ghana and those in South Korea and now, using the same framework as in Baptist and Teal[2008], this time with the pooled African dataset, we consider within-Africa differences. Sector, foreign ownership and export status have all been flagged in the literature as possible mechanisms for development[Söderbom and Teal, 2004]. Dummy variables can be interacted with the technology (ie the input coefficients) to test for technological heterogeneity across these characteristics. A fourth possible explanation, firm size, is not addressed here as it can be incorporated into the generalised technology in Section 4.

Table 2 summarises the pooled dataset on manufacturing firms from five countries used in this paper.[3] The combined sample is an unbalanced panel with not all firms being observed in all years. The firms are classified into 7

[3]This paper draws on data collected as part of the Regional Program on Enterprise Development (RPED), organised by the World Bank and funded by the Belgian, British, Canadian, Dutch, French and Swedish governments. Extensions to this data for Ghana were collected by a team from the Centre for the Study of African Economies, Oxford and the Ghana Statistical Office (GSO), Accra over a period from 1992 to 2003. The surveys have been funded by the Department for International Development of the UK government. The Kenyan, Nigerian and Tanzanian data collection was funded by both DFID and UNIDO. Work on this project was funded by the Economic and Social Research Council of the UK as part of the Global Poverty Research Group.

sectors: food/bakery, metals/machinery/chemical/paper, textiles, garments, wood, furniture and, finally, South African textile and garment firms are classified as a separate sector.

Baptist and Teal(2008) demonstrate (see Table 1) that the form of technology and the return to education are the two key differentials between manufacturing firms in Ghana and those in South Korea. In Table 3 we see a pattern of technological difference across African countries that is consistent with that observed between Ghana and South Korea. Firms are operating from a menu of technologies which differ in their characteristics. Returns to scale do not differ across technologies but there is variation in the output elasticities. Interacting country dummies with the input coefficients and testing the joint significance of the interaction terms shows that there is no difference in the technology used in Ghana, Kenya and Nigeria, but that Tanzania and South Africa are using separate distinct technologies. Interacting dummies for foreign ownership, export status and sector proved insignificant. This is particularly interesting for South Africa as approximately 75% of those firms are in the MetMac sector. So South African firms are not only distinct from those in other countries, but firms in a single sector in South Africa are distinct from firms in the same sector in another country. Thus in our dataset we see three different technologies exhibited.

Countries with higher per-capita incomes are using technologies with a higher output elasticity of labour and a lower output elasticity of materials. In the case of Ghana and South Korea, this difference, along with the different rates of return to education, could fully account for differences in output per worker. We now move to investigate the firm level returns to education in the African data. This data is only available for Ghana, Tanzania and a subset of the Kenyan firms.

The results of including a quadratic education term are presented in Table 4. For each of the two technologies for which we have education data three sets of estimates are presented. The first is a simple OLS estimation, which was shown in Baptist and Teal[2008] to be acceptable for the analogous modelling done in that paper, with the measure of education varying by firm. The second treats education as a firm fixed effect. That is, the annually reported worker education levels for each firm are averaged so that the measure is time-invariant. This has the effect of reducing variance in the education measure and will be preferred if one believes that there is significant measurement error in the education data, or if that human capital embodied in a firm is a long-term characteristic and so will not be contemporaneously

	Ghana	Kenya	Nigeria	South Africa	Tanzania	All
lnY	12.24	13.91	13.66	16.21	12.03	12.58
	(0.16)	(0.14)	(0.24)	(0.10)	(0.16)	(0.10)
lnK	10.98	13.45	12.58	15.18	11.20	11.60
	(0.22)	(0.18)	(0.28)	(0.14)	(0.21)	(0.14)
lnL	3.13	3.58	3.44	4.86	2.89	3.17
	(0.10)	(0.10)	(0.15)	(0.07)	(0.10)	(0.06)
lnO	9.46	11.27	11.19	13.24	9.73	9.95
	(0.20)	(0.14)	(0.27)	(0.11)	(0.17)	(0.12)
lnM	11.42	13.13	12.88	15.38	11.26	11.77
	(0.16)	(0.15)	(0.26)	(0.11)	(0.17)	(0.10)
Educ	9.92	8.51			7.40	8.95
	(0.13)	(0.11)			(0.11)	(0.09)
Anyfor	0.18	0.19	0.20	0.25	0.15	0.17
	(0.03)	(0.03)	(0.03)	(0.04)	(0.02)	(0.02)
Exports	0.17	0.36	0.08	0.65	0.14	0.21
	(0.02)	(0.03)	(0.02)	(0.04)	(0.02)	(0.02)
Firm Age	17.99	21.19	22.03	19.87	15.33	18.05
	(0.83)	(0.93)	(0.93)	(1.43)	(0.83)	(0.53)
Obs (N)	1453	652	535	260	716	2821
Firms	222	294	154	147	298	814
Year Span	1991-2002	1992-1999	1998-2003	1997-1998	1992-2000	

Table 2: Summary statistics for the African Data. The variable definitions are taken from Rankin et al[2006]. Employment is the total number of employees in the firm. Output, capital, raw material and indirect costs are all in 1996 PPP$. The deflation procedure used for Ghana, Kenya and Tanzania was to deflate the nominal values into constant price domestic and then convert into PPP$ using the exchange rates in the Penn World Tables. The deflation for both Ghana and Tanzania used firm based price indices while for Kenya sector level deflators were used. In the case of Nigeria and South Africa the nominal values were deflated by consumer prices, producer prices being unavailable, then converted in US$ using the exchange rate for the base period. These US numbers were then deflated by the PPP deflator to 1996 values. Firm age is in years and any foreign ownership is a dummy which takes the value 1 if the firm has any element of foreign ownership and zero otherwise. Exports is a dummy taking the value 1 if the firm exports, and Educ is the weighted average of years of education of workers in the firm. The Ghanaian data is described more fully in Baptist and Teal[2008] and the Nigerian data in Malik et al[2006]. These summary statistics were calculated over those observations with data on all variables and so those regressions without the full set of variables may include some additional observations. Note also that the standard error of the mean, given in parenthesis, can be converted into the standard deviation of the variable through multiplying by $\sqrt{N}$.

OLS	Tanzania	GKN	South Africa
lnK	0.0362***	0.0739***	0.0747***
	(0.0096)	(0.0085)	(0.0195)
lnL	0.1120***	0.1386***	0.2389***
	(0.0127)	(0.0160)	(0.0345)
lnO	0.2669***	0.1802***	0.1319***
	(0.0251)	(0.0145)	(0.0293)
lnM	0.5849***	0.6074***	0.5545***
	(0.0211)	(0.0249)	(0.0389)
Kenya		-0.0694	
		(0.0454)	
Nigeria		0.0400	
		(0.0533)	
Exports	0.0322	0.0791*	0.0980
	(0.0409)	(0.0321)	(0.0521)
Anyfor	-0.0283	0.0375	0.1088**
	(0.0420)	(0.0369)	(0.0417)
Firm Age	-0.0013	0.0022	0.0001
	(0.0011)	(0.0012)	(0.0015)
MetalMac	-0.0544	-0.0296	0.0812
	(0.0386)	(0.0458)	(0.0933)
Textile	-0.0996*	-0.1270*	
	(0.0462)	(0.0612)	
Garment	-0.0702	0.0009	
	(0.0522)	(0.0554)	
Wood	0.0152	-0.0822	
	(0.0643)	(0.0685)	
Furn	-0.0711	0.0111	0.0912
	(0.0482)	(0.0583)	(0.1083)
TexGarSA			-0.0467
			(0.1243)
Constant	2.1525***	2.2997***	3.4656***
	(0.1071)	(0.1755)	(0.3717)
TechDiff	0.0024	0.5895	0.0478
CRS	0.2148	0.7817	0.3847

Table 3: Cobb-Douglas production functions for 5 African countries. Constant returns to scale have been imposed and the p-value testing this from the unrestricted regression is given as CRS. Food and Bakeries is the omitted sector, and Ghana is the omitted country dummy. Year dummies were included but are not reported. TechDiff is a p-value from a test of technological difference. For Tanzania this test comes from running a regression pooled with GKN, allowing for the coefficients for Tanzania to differ, and the null hypothesis is that the interaction terms on the input coefficients are jointly zero. Similarly for South Africa. For the GKN sample all coefficients were allowed to differ by country and the p-value is a test that all the interaction terms are jointly zero.

affected by the yearly fluctuations in the number of years of schooling of the employees. The third column adapts this approach by including a firm fixed effect along with the time-varying measure of education.

Table 4 is consistent with the results of Baptist and Teal[2008]. There is no significant level TFP difference between the countries (as given by the intercept term), and returns to education (to the firm) are low in Africa. In Tanzania the effect of education is never significantly different from zero. For GKN education is only significant when it is treated as time invariant and then it is as in Table 1: small in magnitude and slightly convex. There is unfortunately no human capital data available for the South African firms but we can impute a rate of return which would be consistent. The intercept for South Africa in Table 3 is 1.2 higher (in logs) than that of the other countries. Assuming an average of 10 years of education for workers in South African manufacturing firms, then an average linear coefficient of 0.1 would close the gap (ie approx. 10% return on each year of schooling). This figure is midway between the corresponding figures for South Korea and Ghana presented in Baptist and Teal[2008]. So, the rate of return that we would need to impose so that South Africa was perfectly consistent with the proposed structure of technology appears plausible.

What does this tell us? Technology is not differing due to sector or firm characteristics, rather, technology differs according to the country in which the firm is located. This suggests that it is factors in the external environment that are associated with choice of technology. In this dataset we observe three different types of technology with a uniform relationship to income per capita in the broader economy. As income per capita rises, then the output elasticity of materials falls, that of labour rises, and the returns to education also rise.

4 Skills and Technology

The Cobb-Douglas functional form is a relatively simple form widely used in empirical analysis, however, it imposes a number of restrictions on technology. For example, output elasticities do not vary with size or factor levels or combinations. This restrictive functional form may be artificially generating technological difference when the true difference lies in scale or factor choice. For example, imagine we have a population of firms with a common translog production function but with half facing different factor prices and

	T OLS	T Av OLS	T FE	GKN OLS	GKN Av OLS	GKN FE
lnK	0.034***	0.033**	0.066*	0.071***	0.066***	0.140***
	(0.010)	(0.010)	(0.028)	(0.009)	(0.010)	(0.018)
lnL	0.113	0.114	0.151	0.119	0.125	0.129
	(0.013)	(0.013)	(0.028)	(0.015)	(0.015)	(0.01)
lnO	0.267***	0.266***	0.209***	0.163***	0.159***	0.127***
	(0.025)	(0.026)	(0.025)	(0.014)	(0.014)	(0.010)
lnM	0.587***	0.587***	0.575***	0.647***	0.649***	0.605***
	(0.021)	(0.021)	(0.022)	(0.018)	(0.018)	(0.010)
Edu	-0.008	-0.000	-0.052	-0.022	-0.116*	0.018
	(0.026)	(0.036)	(0.037)	(0.024)	(0.047)	(0.021)
Edu Sq	0.001	0.001	0.003	0.001	0.007*	-0.001
	(0.002)	(0.002)	(0.002)	(0.001)	(0.003)	(0.001)
Exports	0.034	0.032		0.063	0.064	
	(0.041)	(0.041)		(0.034)	(0.034)	
Anyfor	-0.033	-0.035		0.040	0.046	
	(0.042)	(0.043)		(0.039)	(0.038)	
Firm Age	-0.001	-0.001	-0.059	0.003*	0.003*	-0.070
	(0.001)	(0.001)	(0.105)	(0.001)	(0.001)	(0.126)
MetMac	-0.047	-0.050		0.017	0.020	
	(0.038)	(0.038)		(0.042)	(0.041)	
Textile	-0.098*	-0.098*		-0.062	-0.057	
	(0.046)	(0.046)		(0.049)	(0.049)	
Garment	-0.057	-0.056		0.034	0.041	
	(0.051)	(0.051)		(0.046)	(0.045)	
Wood	0.028	0.029		-0.006	-0.001	
	(0.064)	(0.064)		(0.067)	(0.064)	
Furn	-0.056	-0.058		0.062	0.074	
	(0.047)	(0.048)		(0.054)	(0.053)	
Kenya				-0.092*	-0.068	
				(0.046)	(0.046)	
Constant	2.134***	2.105***	3.483	2.124***	2.533***	3.558
	(0.145)	(0.165)	(1.777)	(0.153)	(0.239)	(2.665)
Educ	0.444	0.357	0.354	0.537	0.037	0.702
Obs	715	715	715	2090	2090	2090
Firms			297			516

Table 4: Cobb-Douglas production functions for 3 African countries including a quadratic education effect. Constant returns to scale have been imposed. Food and Bakery is the omitted sector, and Ghana is the omitted country dummy. Year dummies were included but are not reported. Firms reporting average worker education of over 15 years were excluded. Columns 1 and 3 are OLS estimates, while columns 2 and 4 use the (time invariant) average level of education for each firm. Columns 3 and 6 are fixed effect estimates.

so choosing relatively higher capital stocks. A Cobb-Douglas function form may reject the hypothesis of common technology, whereas a translog function would not. In the context of a Cobb-Douglas production function, a firm cannot embark on a transition along the path identified in Section 3 through increases in scale or factor proportions - it must shift to a new production function.

In this section we generalise the Cobb-Douglas production function to the translog production function.

$$\ln Y = a + \sum_{i=1}^{n} b_i \ln q_i + \frac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{n} c_{ij} \ln q_i \ln q_j. \tag{20}$$

The translog form allows output elasticities to vary with input combinations. In this way we can investigate whether there is a genuine technological switch, or if the Cobb-Douglas differences are simply reflective of firms being on different locations on the same isoquant. Augmenting the translog production function by interacting the time trend with each input tests the hypothesis of secular coefficient evolution over time. Hence we will see whether, through either scale, factor choice or systemic changes over time, African firms are on a path that will lead them to appear like South Korean firms.

The primary attraction of a translog production function is its flexibility from being a general second order approximation, and the fact that it imposes few *a priori* restrictions other than requiring strictly positive input quantities q_i. However, this flexibility comes with some cost. The approximation is only a local one and becomes less accurate as input quantities move further from the expansion point, in this case the unit vector. A further problem is that, unlike the Cobb-Douglas function, the translog is not globally concave and output elasticities (ie first derivatives) are not necessarily always positive. The extent to which these two desirable properties of a production function are met can be evaluated at any given input vector. The approximation is often said to be 'acceptable' if these two properties hold for a 'sufficient' number of points over the observed input range.

Technological progress is an important component of production theory, and needs to be incorporated into the production function. Despite significant literature surrounding the notion of technical progress, the most commonly used econometric representation is the inclusion of a simple time trend [Doucouliagos and Parikh, 2000, Gajanan and Ramaiah, 1996, Turnovsky et al., 1982]. In order to investigate possible trends in both TFP and in technology, technological progress is allowed to affect individual factors at different exponential rates. Thus technological progress becomes linear when expressed in logarithmic terms. Hicks-neutral technological progress, where the coefficient is the same on each input, is tested for. Such linear characterisations of technology are clearly inappropriate over very long time horizons and need to be viewed as linear approximations over the time period concerned. In the event that evidence for significant technological progress is identified this approximation will need to be reviewed. $\sum_{i=1}^{n} d_i$ will indicate if the returns to scale are changing over the time period. If this quantity is positive, then it is indicative that returns to scale in African manufacturing are increasing in magnitude over time and could be the source of secular productivity gains. The second-order, technology-adjusted translog production function is then:

$$\ln Y = a + \sum_{i=1}^{n} b_i \ln q_i + \frac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{n} c_{ij} \ln q_i \ln q_j + \sum_{i=1}^{n} d_i t \ln q_i. \tag{21}$$

Also included in the estimation equation is firm age, along with dummies for each year-country combination, sector, any foreign ownership, and whether the firm exports.

The translog functional form allows for various properties of a production function to be tested for. These properties include the Cobb-Douglas form, homogeneity, returns to scale, separability, technical progress and the value-added specification. It is clear by inspection that, if all the c_{ij} are zero, equation 21 reduces to the familiar Cobb-Douglas form.[4] Using the definition that a function f is homogenous of degree θ if $f(tX) = t^{\theta} f(X)$ it follows that a translog production function will be homogenous of degree θ if $\sum_{i=1}^{n} b_i = \theta$ and $\sum_{i=1}^{n} c_{ij} = 0 \, \forall j$. If, in addition to homogeneity, $\theta = 1$ the function also exhibits constant returns to scale, or, equivalently, linear homogeneity. More generally, for a homogenous function, θ is an estimate of the returns to scale of the technology.

There are a number of ways in which human capital can be incorporated into the production function. The most simple is as a pure level effect, as modelled in Table 4. However that method does not consider possible interactions with the production function coefficients, which the results so far suggest are often important. Human capital may be incorporated into the technology through its inclusion as a completely separate input, or through an appropriate transform of the labour quantity input. The latter approach

[4] $Y = A q_K^{b_K + d_K t} q_L^{b_L + d_L t} q_E^{b_E + d_E t}$, where $A = e^a$.

is pursued here so as to prevent the production function becoming too cumbersome, although there is some loss of generality in doing so. The particular transform used is to multiply the number of workers by the average years of education of workers at the firm before taking the natural logarithm.[5]

Tables 1 and 3 show that firms in different countries use different technologies but all operate under constant returns to scale. The translog framework allows for this result to be probed in more detail[6]. For example, it is possible that the same non-homogenous translog production function underlies firms in both countries. For a non-homogenous function output elasticities will differ with input combinations. So, given that South Korean firms use substantially different input combinations (in this scenario perhaps due do factor prices), it is possible that incorrectly approximating with a Cobb-Douglas function will give the appearance of different technologies. If this is the case, then we would expect African firms to look like South Korean ones as their input ratios and levels become more like those of South Korean firms. Alternatively, if the technology is homogenous but of degree significantly greater than unity, then increases in input levels could lead to productivity convergence. If hypotheses such as these turn out to be supported, then the policy relevance is not with technology choice, but with increasing the scale of African firms and ensuring that factor prices are not distorted. However, at the other extreme, if African firms are using a linearly homogenous technology, then a technological switch will be required.

Production functions also have a set of separability properties. Two inputs i and j are said to be separable from a third input k if $\frac{\partial}{\partial q_k}\frac{\frac{\partial f}{\partial q_i}}{\frac{\partial f}{\partial q_j}} = 0$. In the translog framework this condition reduces to $c_{ik} = c_{jk} = 0$[7]. If inputs are found to be separable then restrictions can be placed upon the functional form to improve the efficiency of the analysis. Analogous definitions hold for global separability (where all inputs are separable from each other) and pairwise separability. The most relevant form of pairwise separability is that

[5]Note this is implicitly assuming a linear return to education which, as we have seen, is a fairly accurate approximation for Africa.

[6]Note that, although the tests are not presented for reasons of brevity, the same country groups of technology difference persist in the translog.

[7]Technically this condition is sufficient but not necessary, however, the conditions under which it is not necessary are sufficiently restrictive that they can be ignored. The necessary and sufficient condition is that $s_j c_{ik} - s_i c_{jk} = 0$. As factor shares s_i and s_j must be positive it is clear how the sufficient condition noted above follows.

of capital and labour from materials and indirect inputs. This is a necessary, but not sufficient, condition for a value-added specification to be valid. Thus testing of this particular form of pairwise separability will indicate whether the value-added specification should be investigated.

The translog form will also allow some comment to be made upon substitution between inputs. While there is no unambiguous definition of the elasticity of substitution in a multi-input framework, any measure of substitutability will be dependent upon the cross-derivative of output with respect to the two inputs, which, in the translog framework, will be the coefficient on the interaction term c_{ij}. Comparing the signs of the cross-derivatives will indicate how the marginal productivity of one input is affected by changes in the input level of another. For example, if this coefficient was positive, it would be evidence to suggest that the inputs are complements. An increase in the level of input i would then increase the marginal productivity of input j which, in turn, would *a priori* cause the optimising firm to increase the level of input j. This second indicator of the elasticity properties is of course not dependent upon input levels but does provide an intuitive reason as to why consideration of the second derivative is an appropriate way to consider substitution possibilities.

Endogeneity is still a concern and so fixed effects, difference GMM and system GMM estimators are explored as possible mechanisms to remove any bias from unobserved factors being correlated with observable inputs. Fixed effects estimation will remove any bias caused by firm-specific time-invariant unobservables, while the inclusion of year dummies will account for time-specific unobservables. However the fixed effects estimator will still be subject to endogeneity bias from firm-specific time-varying factors. The system GMM estimator of Arellano and Bond[1991] is used in an attempt to control for this latter type of endogeneity bias. This estimator exploits the autocorrelation structure of the residuals to provide instruments. Sufficiently lagged differences are used as instruments for contemporaneous levels while lagged levels are instruments for the equation in first differences. All standard errors are robust to heteroskedasticity and autocorrelation. In addition, the standard errors for the OLS regression have been calculated using a clustering method that allows for the errors to be correlated within firms observed in multiple time periods but independent between firms.

The input coefficients from the translog are presented in Table 5. The signs of the material cross-input terms are all negative, and are the only significant cross terms, suggesting that materials are substitutable with all

	Tanz OLS	Tanz FE	Tanz GMM	GKN OLS	GKN FE	GKN GMM
b_K	-0.0059	-0.0946	-0.1447	0.2182***	0.2802*	0.0404
	(0.0504)	(0.1864)	(0.2343)	(0.0534)	(0.1277)	(0.1331)
b_L	0.1330	0.0682	0.0568	0.2862***	0.2532*	0.5394 **
	(0.0866)	(0.1860)	(0.3534)	(0.0693)	(0.1218)	(0.1885)
b_O	0.7690***	0.8483***	0.7595*	0.2190**	0.3022***	0.2057
	(0.1129)	(0.1592)	(0.3800)	(0.0790)	(0.0763)	(0.1198)
b_M	0.0217	0.1647	0.2579	0.3549***	0.4308***	0.4821 ***
	(0.0972)	(0.1518)	(0.3178)	(0.0815)	(0.1026)	(0.1347)
c_{LL}	0.0253	0.0566	-0.1042	0.0501**	0.0547	0.0372
	(0.0286)	(0.0351)	(0.1019)	(0.0184)	(0.0295)	(0.0461)
c_{KK}	0.0071	0.0396	0.0040	0.0307**	0.0382*	0.0213
	(0.0090)	(0.0208)	(0.0301)	(0.0111)	(0.0187)	(0.0190)
c_{MM}	0.1604***	0.1764***	0.1958*	0.1466***	0.1345***	0.1256 ***
	(0.0273)	(0.0364)	(0.0921)	(0.0185)	(0.0152)	(0.0260)
c_{OO}	0.1121**	0.1434*	0.0324	0.0793***	0.0529***	0.0853 ***
	(0.0351)	(0.0658)	(0.1443)	(0.0114)	(0.0104)	(0.0200)
c_{KL}	0.0144	-0.0141	0.0771*	0.0119	-0.0003	0.0171
	(0.0126)	(0.0183)	(0.0363)	(0.0092)	(0.0156)	(0.0187)
c_{LM}	-0.0402*	-0.0279	-0.1519**	-0.0430**	-0.0250	-0.0812 **
	(0.0194)	(0.0309)	(0.0506)	(0.0141)	(0.0191)	(0.0282)
c_{LO}	0.0096	0.0118	0.1120	-0.0046	-0.0191	0.0180
	(0.0252)	(0.0429)	(0.0762)	(0.0109)	(0.0121)	(0.0186)
c_{KM}	-0.0009	-0.0009	-0.0268	-0.0482***	-0.0615***	-0.0147
	(0.0100)	(0.0162)	(0.0339)	(0.0130)	(0.0147)	(0.0175)
c_{KO}	-0.0105	-0.0190	-0.0065	0.0015	0.0125	-0.0139
	(0.0124)	(0.0203)	(0.0413)	(0.0081)	(0.0083)	(0.0138)
c_{OM}	-0.1180***	-0.1543***	-0.0820	-0.0690***	-0.0617***	-0.0692 **
	(0.0266)	(0.0404)	(0.1089)	(0.0154)	(0.0133)	(0.0220)
Constant	2.9083***	6.6471	2.9755***	1.6244***	2.2425	1.1782 *
	(0.2451)	(7.6654)	(0.8444)	(0.2723)	(1.6564)	(0.4835)
AR1		0.0079	0.0913		0.0000	0.0000
AR2		0.2945	0.0138		0.0034	0.0033
AR3		.	.		0.0454	0.0419
Sargan			58.5093			163.04
Sargandf			68			447
Sarganp		.	0.7873			1.0000
Obs	716	720	716	2105	2125	2105
Firms		302	298		517	516

Table 5: Input coefficients from an unrestricted translog production function.

other inputs. The apparent substitutability of materials with other inputs is a major feature of the production function. This provides support for the idea that using a technology that is material-intensive provides African firms with more flexibility and thereby for the hypothesis of endogenous technology choice outlined in Section 2.

The diagnostics in Table 5 suggest that the GMM instrument sets are not dealing with endogeneity in an ideal manner. There is strong evidence of AR2 and weak evidence of AR3. AR3 would render the instrument sets used invalid as three-period lags have been assumed to be uncorrelated with the contemporaneous unobservables. The Sargan statistic is also suggestive of overfitting as the p-value is very high, even using the restricted instrument set proposed by Bowsher[2001]. However, Baptist and Teal[2008] carried out a more extensive analysis of endogeneity in the Ghanaian data, and found that the patterns of the coefficients remain remarkable robust across a range of methodologies for correcting for endogeneity. For the purposes of this paper it is generally not critical to know the exact magnitude of the coefficients, we are more interested in the overall pattern. The OLS estimates are the basis for the analysis but, recognising that they may be biased by unobservables, the FE and GMM estimates give an indication of the possible direction and magnitude of the bias.

The translog production function contains a wealth of potential information, however, we wish to focus upon the implications for technological change. Much useful data to this end is contained in Tables 6 and 7: the coefficients d and the tests of technological progress. The contrast between Tanzania and GKN is particularly instructive. According to the Penn World Tables 6.2 over the period 1991-2003, the widest range in our data, real GDP per capita in Tanzania grew by a total of 132%. Of the countries in our sample the next highest growth rate was that of Ghana at 53%. Using PPP-adjusted GDP per capita as the measure, Tanzania was also the poorest country in the sample. At the start and end of the period its GDP per capita was 56% and 23% respectively below that of Nigeria, the next poorest. Note that the year dummies, although not reported for brevity, mirror this trend. They suggest that firms in Tanzania were 156% more productive at the end of the period, while those in the other countries showed no significant change (and, in fact, a small insignificant negative change)[8]. So we have the poor-

[8]The PWT data is for the whole economy whereas our data is only for manufacturing firms. The fact we see no TFP growth in firms in Ghana and Nigeria but some GDP

	Tanz OLS	Tanz FE	Tanz GMM	GKN OLS	GKN FE	GKN GMM
d_K	-0.0003	-0.0066	0.0201*	-0.0056*	-0.0110***	-0.0028
	(0.0025)	(0.0041)	(0.0091)	(0.0028)	(0.0029)	(0.0054)
d_L	0.0067	0.0149	0.0483*	-0.0091*	0.0008	-0.0150
	(0.0049)	(0.0084)	(0.0223)	(0.0041)	(0.0048)	(0.0092)
d_O	-0.0308***	-0.0269**	-0.0676*	0.0030	0.0024	0.0024
	(0.0066)	(0.0086)	(0.0277)	(0.0039)	(0.0037)	(0.0074)
d_M	0.0193**	0.0175*	0.0051	0.0083	0.0096**	0.0062
	(0.0064)	(0.0083)	(0.0225)	(0.0045)	(0.0034)	(0.0041)
Exports	0.0016		-0.1166	0.0391		0.0168
	(0.0398)		(0.0952)	(0.0310)		(0.0523)
Anyfor	0.0047		-0.0138	0.0309		0.0097
	(0.0366)		(0.1225)	(0.0389)		(0.0835)
Firm Age	-0.0010	-0.0852	-0.0043	0.0024*	-0.0221	0.0047 *
	(0.0009)	(0.1476)	(0.0028)	(0.0010)	(0.0225)	(0.0022)
MetMac	-0.0088		-0.0350	0.0757*		0.1132 *
	(0.0310)		(0.0577)	(0.0359)		(0.0444)
Textile	-0.0876*		0.0152	0.0027		0.0418
	(0.0440)		(0.1451)	(0.0399)		(0.0581)
Garment	-0.0160		-0.0619	0.0692		0.1239 *
	(0.0424)		(0.0823)	(0.0371)		(0.0553)
Wood	0.0170		0.0100	-0.0290		0.0324
	(0.0534)		(0.0959)	(0.0576)		(0.0698)
Furn	-0.0170		-0.0846	0.1358**		0.1842 **
	(0.0389)		(0.0723)	(0.0461)		(0.0568)
Kenya				-0.0316		-0.0360
				(0.0495)		(0.0650)

Table 6: Technical Change and Firm Characteristics from a translog production function.s

est country in our sample using a distinct technology and growing rapidly - surely instructive for investigating technological change.

Looking at the coefficients d in Table 6 we can see that, for Tanzania, the major change over time has been a fall in the intensity with which 'other inputs' are used. More broadly, taken together, the share of raw materials and other inputs in production has been falling, while that of capital and labour has been rising. In GKN, where there was no substantial growth, the effects are at best insignificant if not the reverse. The absolute value of the statistic TechProg in Table 7 tells us how returns to scale have been changing over time and this effect has been small and likely negative. So the evidence from comparing the rapidly growing Tanzania with GKN is that there have not been changes in returns to scale, but weight is shifting between the coefficients in precisely the direction we would expect.

This is not to say that there is no interest in considering the returns to scale of the firms. The translog function allows returns to scale to vary by input coefficients. All other things being equal we may expect that smaller firms are more likely to exhibit increasing returns to scale or, if technology is at least locally CRS, for there to be no relationship. Figures 1 and 2 graph returns to scale versus the natural logarithm of average firm employment. For GKN we see no relationship but, for Tanzania, returns to scale are actually *increasing* in firm size. This is consistent with Tanzanian firms, as they grow, moving to a point where they switch from a technology intensive in the use of variable factors to one intensive in the use of fixed factors. As they near the point where they want to switch, they face capacity constraints using their existing technology and so we see increasing returns to scale.

By definition, a production function with constant returns to scale is linearly homogenous, and so the fact that we observe the former (on average) while being able to reject the latter is an apparent contradiction. This can be resolved by noting that the test for homogeneity in Table 7 is a global test, whereas the calculations of returns to scale are calculated at specific points in the input space. Returns to scale will not be identical (or constant) across the entire input space if the function is non-homogenous, but they may be identical (or constant) across a subset of input combinations. The estimated function here evidently has returns to scale close to unity for the input bundles observed, but not across the entire input space. The

growth suggests that the growth was in the non-manufacturing sectors of the economy, such as Cocoa or Oil.

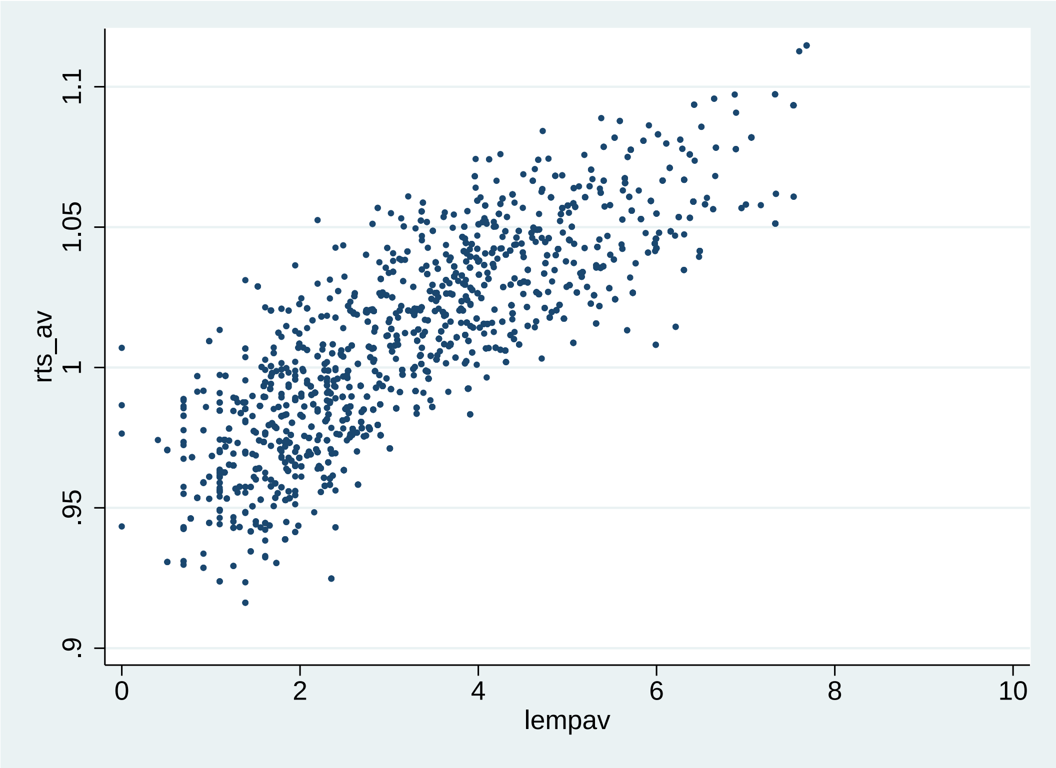

Figure 1: Returns to scale vs Employment in Tanzania

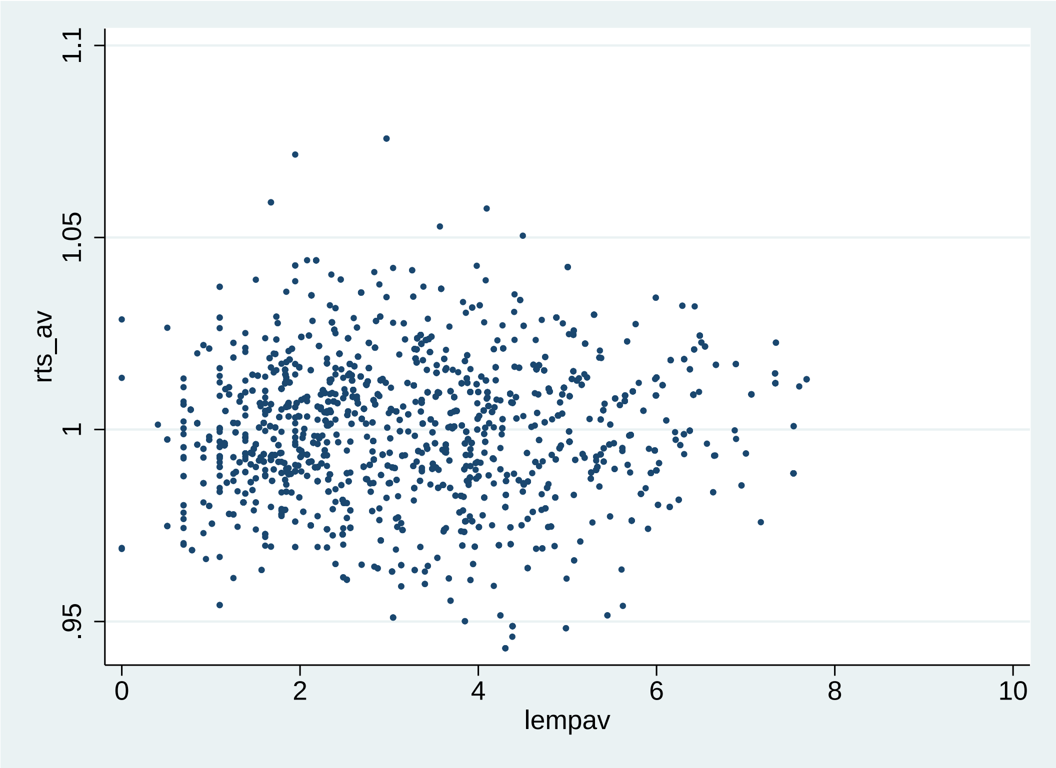

Figure 2: Returns to scale vs Employment in GKN

	T OLS	T FE	T GMM	GKN OLS	GKN FE	GKN GMM
CobbDouglas	0.0000	0.0000	0.0001	0.0000	0.0000	0.0000
KInteract	0.0101	0.0056	0.0477	-0.0041	-0.0111	0.0097
LInteract	0.0092	0.0264	-0.0670	0.0143	0.0102	-0.0090
IInteract	-0.0067	-0.0180	0.0558	0.0071	-0.0154	0.0201
MInteract	0.0013	-0.0068	-0.0649	-0.0137	-0.0137	-0.0395
Homog	0.0047	0.2745	0.0655	0.3821	0.0547	0.2656
DegHomog	0.9178	0.9866	0.9295	1.0783	1.2664	1.2677
LinHomog	0.0001	0.3413	0.0811	0.4139	0.0234	0.1152
GlobalSep	0.0000	0.0001	0.0004	0.0000	0.0000	0.0000
CapSep	0.5688	0.5945	0.1890	0.0035	0.0001	0.5363
LabSep	0.0631	0.4231	0.0039	0.0021	0.0210	0.0341
IndSep	0.0001	0.0019	0.4047	0.0000	0.0000	0.0023
MatSep	0.0000	0.0000	0.0003	0.0000	0.0000	0.0000
VAD	0.0925	0.7344	0.0281	0.0001	0.0000	0.0284
TechProg	-0.0051	-0.0012	0.0059	-0.0034	0.0019	-0.0092
Hicks	0.0003	0.0091	0.0020	0.0076	0.0002	0.1277
No TP	0.0000	0.0015	0.0023	0.0077	0.0003	0.0017
Monot	0.8671	0.4135	0.3145	0.7678	0.5937	0.5539
Qconv	0.5262	0.2511	0.2475	0.5612	0.3553	0.4161
Reset	0.1097			0.0033		

Table 7: Specification tests on an unrestricted translog production function. All entries are p-values unless otherwise specified. CobbDouglas is testing the null hypothesis that the production function is Cobb-Douglas. KInteract is the quantity $\sum_j c_{Kj}$, with similar definitions for other inputs. Homog is the null hypothesis of homogeneity of any degree, while LinHomog is the null hypothesis of linear homogeneity. Homog reports the point estimate of the degree of homogeneity. GlobalSep tests the null that the production function is globally separable, while CapSep tests the null that capital is separable from other inputs with analagous definitions for other inputs. VAD test the null that capital and labour are jointly separable from other inputs. TechProg reports the magnitude of $\sum_i d_i$. Hicks tests the null of Hicks-neutral technical progress ($d_i = d \forall i$) while NoTP tests for $d_i = 0 \forall i$. Reset is the p-value from a Ramsey Reset test with the null of no omitted variables.

implications of this non-homogeneity, therefore, are dependent upon how it affects the properties of the function across the relevant input space. Note that the definition of the relevant input space will change depending upon the question being addressed and may extend beyond the observed range. For example, the relevant input space here will include that observed in the South Korean firms.

Taking the first derivative of Equation 21 it can be seen that, for each input i, the sum of the coefficients on the interaction terms, $\sum_j b_{ij}$, give what will happen to the output elasticities as input levels rise. The sum of these terms are given in Table 7. The clearest pattern is for this quantity to be negative for M suggesting that, as the input levels of firms rise, we will observe a small reduction in the material elasticity of output. The quantity for capital is also positive in Tanzania, while the inconclusive pattern of the other inputs across estimation methods means that we are cautious in drawing more specific conclusions.

Given that so many authors implicitly assume that materials are separable from capital and labour inputs, is it possible to develop some intuition as to how materials may interact with these inputs? There are previous empirical studies in other contexts that provide evidence for material substitution. For example, Campbell and Jennings[1990], in an econometric study of the Tasmanian sawmilling industry, find significant capital-material substitution. In this context it is easy to imagine purchasing machinery that allows for raw logs to be sawn in such a way so as to obtain more planks. Output could then be maintained with a reduced level of material inputs. A similar argument can be applied to many manufacturing firms. For example, a garment firm may have the option to purchase a more sophisticated piece of equipment that can cut and sew with greater accuracy thereby allowing more shirts to be cut out of a given length of cloth.

Another innovation that would result in capital-material substitution is that of just-in-time inventory systems. Excess supplies of raw materials represent a cost to the firm, such as through storage costs and cash-flow restrictions, and so they will generally wish to minimise stocks. However, the risk of running out of a key material due to poor inventory management will induce firms to hold a buffer of materials. Investment in inventory management systems (capital) that enable more effective management of inventories will allow firms to reduce their inputs of materials due to the investment.

It is similarly plausible to imagine substitution between materials and labour. Workers in a textile firm with more employees will be able to be more specialised and hence reduce wastage from production errors. More highly skilled workers may also be able to use materials in a more efficient way, such as through managing stocks at a bakery to reduce losses through perishable ingredients spoiling, in the same way that they may operate and maintain machinery more effectively.

Although Table 7 rejects the Cobb-Douglas restriction, the technology difference persists in the translog. So the first order approximation of the Cobb-Douglas was not falsely identifying difference. Although the interaction terms are jointly significant, the Cobb-Douglas is still useful as it is easier to interpret and can succinctly present some of the salient features. We can turn to the translog where it provides useful extra information. Doing this we see that there is a technological difference between firms in these country groupings, and that this is not the result of scale, factor proportions, or secular coefficient evolution over time. Firms are not engaged in a transition along an expansion path and, given that they use different technologies which are correlated somehow with income per capita, this is highly suggestive of technological switches being an important part of the development process.

This quantitative investigation of technology across 6 countries has led to a consistent picture of technology. Broadly, we see an intercept/TFP term of approximately 2 (in 1996 PPP$) everywhere, with the output elasticities, ie the βs, and the return on education differing by levels of income per capita. The evidence presented here is suggestive of the output elasticities and the return on education being jointly determined. A higher rate of return to education, and thus higher wages and improved living standards, is closely linked to a technology switch.

5 Conclusions

The theoretical suggestions put forward in Section 2 have found significant empirical support. African technology is relatively more intensive in its use of variable inputs and less intensive in its use of fixed factors. Moreover, we have seen that the variable factors (loosely, O and M) are substitutable with other inputs, consistent with the idea that a material-intensive technology is more flexible and can insulate the firm from shocks. The ways in which the fastest growing country in this sample, Tanzania, differs from the others is also instructive. In Tanzania returns to scale are positively associated with firm size and the share of raw materials has been decreasing over time.

Neither of these effects were observed in the other firms. In addition the technological differences across countries are also observed when the analysis is restricted to a single manufacturing subsector.

We have established a link between technology choice and development, but we have not shown causation in one direction or the other. It seems reasonable to expect that they are somewhat jointly determined, influenced by what is termed the general 'investment climate'. That Tanzania has grown so rapidly in this period suggests that development can occur without a technological shift, however, we never observe a country using a 'smaller' technology with a higher level of per capita income than a country using a 'larger' technology. We can imagine that, as an economy grows, at some point firms will want to switch, for example: as better access to credit reduces insolvency risk and so makes the larger technology more attractive, as factor prices adjust (eg farm wages rise and so firms want to get a higher marginal product out of workers, or political stability makes the cost of capital fall), or, as the quality of education improves to the point where there are sufficient skilled workers to exploit the larger technologies.

Technology differs systematically by stage of development and technological choice is an example of a specific mechanism which can account for the importance of the 'investment climate'. Countries with lower levels of GDP per capita use a technology in which the output elasticity of labour is lower, that of materials is higher, and in which the firm returns to worker education are low. Rising incomes are associated with increased returns to education and a production process more intensive in its use of fixed factors. Technology, in the specific way in which it is defined in this paper, is critical to the development process. The manufacturing sector, which has been central to almost every successful development experience, cannot achieve sustained increases in output per worker without shifts in technology. It is these increases in output per worker that, in turn, lead to sustainable increases in the incomes of workers and of the owners of capital.

References

[Abel and Eberly, 1999] Abel, A. and Eberly, J. (1999). The effects of irreversibility and uncertainty on capital accumulation. *Journal of Monetary Economics*, 44:339–377.

[Arellano and Bond, 1991] Arellano, M. and Bond, S. (1991). Some Tests of Sepcification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations. *Review of Economic Studies*, 58:277–297.

[Bigsten et al., 2003] Bigsten, A., Collier, P., Dercon, S., Fafchamps, M., Gauthier, B., Gunning, J. W., Oduro, A., Oostendorp, R., Pattillo, C., Söderbom, M., Teal, F., and Zeufack, A. (2003). Credit Constraints in Manufacturing Enterprises in Africa. *Journal of African Economies*, 12(1).

[Bleaney, 1996] Bleaney, M. F. (1996). Macroeconomic Stability, Investment and Growth in Developing Countries. *Journal of Development Economics*, 48:461–477.

[Bowsher, 2002] Bowsher, C. G. (2002). On testing overidentifying restrictions in dynamic panel data models. *Economics Letters*, 77:211–220.

[Campbell and Jennings, 1990] Campbell, H. F. and Jennings, S. M. (1990). Technology and Input Demand in the Tasmanian Sawmilling Industry. *Australian Economic Papers*, 29(55):272–282.

[Caselli and Coleman, 2006] Caselli, F. and Coleman, II, W. J. (2006). The World Technology Frontier. *American Economic Review*, 96(3):499.

[Collier, 2007] Collier, P. (2007). *The Bottom Billion*. Oxford University Press, Oxford.

[Deardorff, 2001] Deardorff, A. V. (2001). Rich and Poor Countries in Neoclassical Trade and Growth. *The Economic Journal*, 111:277–294.

[Doucouliagos and Parikh, 2000] Doucouliagos, H. and Parikh, A. (2000). A Regional Analysis of Technical Change in Australian Manufacturing. *Australian Economic Papers*, 39(2):184–99.

[Elberfeld and Götz, 2002] Elberfeld, W. and Götz, G. (2002). Market Size, Technology Choice, and Market Structure. *German Economic Review*, 3(1):25–41.

[Gajanan and Ramaiah, 1996] Gajanan, S. N. and Ramaiah, K. C. (1996). An Econometric Estimation of Hicksian and Marshallian Elasticities in Indian Manufacturing. *Southern Economic Journal*, 63(2):406.

[Grossman and Helpman, 1995] Grossman, G. M. and Helpman, E. (1995). Technology and Trade. In Grossman, G. M. and Rogoff, K., editors, *Handbook of International Economics. Volume 3*, pages 1279–1337. Elsevier.

[Habyarimana, 2003] Habyarimana, J. (2003). The Benefits of Banking Relationships: Evidence from Uganda's Banking Crisis. mimeo, Harvard University.

[Hubbard, 1994] Hubbard, R. G. (1994). Investment Under Uncertainty: Keeping One's Options Open. *Journal of Economic Literature*, 32:1816–1831.

[Ibarra, 1995] Ibarra, L. A. (1995). Credibility of Trade Policy Reform and Investment: The Mexican Experience. *Journal of Development Economics*, 47:39–60.

[Jones, 2005] Jones, C. I. (2005). The Shape of Production Functions and the Direction of Technical Change. *The Quarterly Journal of Economics*, 120(2):517–549.

[Lambson, 1991] Lambson, V. E. (1991). Industry Evolution with Sunk Costs and Uncertain Market Conditions. *International Journal of Industrial Organization*, 9(2):171–196.

[Malik et al., 2006] Malik, A., Teal, F., and Baptist, S. (2006). The Performance of Nigerian Manufacturing Firms: Report on the Nigerian Manufacturing Enterprise Survey 2004. United Nations Industrial Development Organisation Report.

[Pack, 1993] Pack, H. (1993). Productivity and Industrial Development in Sub-Saharan Africa. *World Development*, 21:1–16.

[Rankin et al., 2006] Rankin, N., Söderbom, M., and Teal, F. (2006). Exporting from Manufacturing Firms in Sub-Saharan Africa. *Journal of African Economies*, 15(4):671–687.

[Servϑn, 1997] Servϑn, L. (1997). Irreversibility, Uncertainty and Private Investment: Analytical Issues and Some Lessons for Africa. *World Bank Working Paper Series*, 1722.

[Söderbom and Teal, 2004] Söderbom, M. and Teal, F. (2004). Size and Efficiency in African Manufacturing Firms: Evidence from Firm-level Panel Data. *Journal of Development Economics*, 73:369–394.

[Turnovsky et al., 1982] Turnovsky, M., Folie, M., and Ulph, A. (1982). Factor Substitutability in Australian Manufacturing with Emphasis on Energy Inputs. *Economic Record*, 58(160):61–72.