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Why do South Korean firms produce so much more output per worker than Ghanaian ones?

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Abstract

The labour productivity differentials between manufacturing firms in Ghana and South Korea exceed those implied by macro analysis. Median value-added per employee is nearly 40 times higher in South Korea than Ghana. The most important single factor in explaining this difference is the Mincerian return to skills which differ by a factor of three between Ghana and South Korea. There is no significant difference in total factor productivity across the countries once we allow for human capital. Our results are consistent with those who have argued that rises in the return to education within developed countries can be explained by skill-biased technical progress in those economies. They are also consistent with work in developing countries which finds a convex return to education based on individual labour market data. Allowing for differences in the shape of the relationship between productivity and human capital across countries is crucial for understanding the role of human capital in increasing productivity.

JEL Classification: O14, D24.

Keywords: African and Asian manufacturing, productivity, efficiency, human capital.

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All remaining errors are ours.
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1 Introduction

High-income countries differ from low-income ones in many dimensions. A long tradition of dual economy models has drawn attention to the central fact of development which is the decline in the share of agriculture in GDP as incomes rise. High income societies have much higher levels of human capital, a larger proportion of their workforce in urban areas and use a quite different range of production techniques than low-income societies, see Temple (2005) for a recent review of the dual economy literature. However the dominant tradition in recent empirical work on the role of technology in explaining differences in income has been to focus, not on these structural differences across economies, but to use an aggregate production function in a tradition which dates back to Solow's (1957) classic paper.

A large body of empirical work has used a Cobb-Douglas version of a production function which incorporates both physical and human capital:

[1] $$V_{it} = K_{it}^{\alpha}(A_{it}H_{ih})^{(1-\alpha)}e^{u_{it}}$$

where V_{it} is value-added, K_{it} is a measure of physical capital, H_{it} is the amount of human capital augmented labour used in production, A_{it} is total factor productivity and u_{it} is the error term.

The potential importance of human capital in the growth process is a focus of much of the endogenous growth literature, Acemoglu (1996), Aghion and Howitt (1998) and Lucas (2002). The problem with translating these growth models into an empirical form for testing, and in generalising from micro studies, is that human capital needs to be measured in a manner that makes it comparable across countries. Our innovation in this paper is to use a sufficiently general functional form that allows both average and marginal returns to human capital to differ across firms within each country.

By extending the basic Solow model to include human capital equation [1] ensures that the A_{it} term, which is total factor productivity (TFP), is all factors other than measurable human and physical capital. An extensive literature at the macro level has argued that if we are to understand differences in incomes across countries the key is to understand what drives this measure of TFP. Hall and Jones (1999) argue for social capital, Lucas (2002) for externalities from human capital and other authors for a very large number of factors. Durlauf et al (2005) list no fewer than 145 variables which have been included in reduced form macro growth models.

A similar conclusion has been derived from work using micro firm-level data. For example the extensive work carried out by the World Bank on firm surveys has been used to argue that the investment climate, by which is meant a range of factors affecting the TFP of firms, "matters enormously and the relative impact of the various investment climate variables indicates where reform efforts should be directed", abstract from Escribano and Guasch (2005). Using micro data there has been extensive investigation of how productivity links to exporting (Bigsten et at 2004, Aw and Hwang 1995, Clerides at al 1998) but much more limited attempts to directly compare the productivity of firms across countries.

Such comparisons are clearly difficult. How outputs and inputs are to be valued and to be made comparable across firms within a country is an important empirical issue in assessing whether returns to scale or market power is being identified. The problem of comparing firms across countries offers even greater empirical challenges. However it needs to be noted that the challenges of using macro data are far greater. As Temple (2005) stresses the move from one to two sector models is a very large increase in the complexity of any analysis of the growth process. In this paper we seek to present a direct comparison of firm-level productivity across Ghanaian and South Korean firms, where we have sought to ensure as great a degree of comparability as possible across the firms. Our question mirrors that posed in the macro analysis by Hall and Jones (1999): why do South Korean firms produce so much more output per worker than Ghanaian ones?

In the next section we set out how, within the context of a standard Cobb-Douglas production function, we can answer that question by identifying the factors that may explain these differences: is it technology, factor intensity, TFP, skills or returns to scale? The data is set out in section 3 where we will show labour productivity differentials at the micro level exceed those at the macro. In section 4 we present models of the production functions for the two countries which allow for differences in technology and in the returns to skill. While a focus on manufacturing is clearly a narrow focus relative to work at the macro level we narrow the base of the comparison still further in section 5 and look at production functions for one sector: textiles and apparel. We also present robustness checks as to how successfully we have allowed for the endogeneity problems that are posed in identifying the parameters of the production function. In section 6 we answer the question posed in the paper's title. A final section concludes.

2 Scale, skills and technology

Production functions such as equation [1] impose constant returns to scale. This restriction is not necessary and is one that we test for in our data. As will be shown below the scale on which Ghanaian and Korean firms operate is very different. If constant returns to scale do hold in the context of a common homothetic technology then the implication is that Ghanaian firms can "scale-up" and, apart from the scale of operation, nothing will change as regards productivity or factor proportions. One reason why it might be argued such a scaling-up is not feasible, even in such a context, is that skills interact with technology in a way not captured by the specification chosen in [1]. In particular Caselli and Coleman (2006) have pointed out that the specification imposes the assumption that workers with different educational achievements are perfect substitutes. They argue that this is clearly rejected by the macro data.

Our micro data is from Ghana and South Korea. Whilst it is reasonable to assume that both the quantity and quality of the education differ substantially across the two countries, it is less clear how important are differences within and between the manufacturing sectors of the countries. The approach adopted by Caselli and Coleman (2006) is to classify workers as skilled or unskilled and to adopt a CES form of the production function. We propose to retain the Cobb-Douglas form of the production function but to use our data on labour quality to measure human capital directly using the same specification as that of Hall and Jones (1999) and Bils and Klenow (2000).[1] In contrast to their approach, which imposes the return on human capital from other sources, we allow the micro data to assess how the return to education differs across the countries in their manufacturing sectors. This has the advantage of allowing the data to determine if the returns to skills are higher in a more capital/technology intensive environment which the extensive discussion of skill biased technical change in the labour market literature suggests may well be possible. We will also allow the other parameters of the production function to differ across the two countries. As in Hall and Jones (1999) we link human capital to years of education by the following functional form:

[2] $$H_{it} = e^{\phi(E_{it})} L_{it}$$

where E_i is the number of years of education of workers in the labour force.

In empirical work the function ϕ is usually written in a form non-linear in the variables as:

[3] $$\phi(E_{it}) = \delta_0 + \delta_1 E_{it} + \delta_2 E_{it}^2 + v_{it}$$

The implied value-added production function is:

[4] $$LnV_{it} = \alpha LnK_{it} + (1-\alpha)LnA_{it} + (1-\alpha)\phi(E_{it}) + (1-\alpha)LnL_{it} + u_{it}$$

which can be re-arranged in per capita terms as:

[5] $$Ln\frac{V_{it}}{L_{it}} = \alpha Ln\frac{K_{it}}{L_{it}} + (1-\alpha)LnA_{it} + (1-\alpha)\phi(E_{it}) + u_{it}$$

This specification ensures that human capital acts as a shifter of the production function in the same way as TFP captured in A_{it}. The argument has been widely advanced at the macro level that education cannot explain the very large differences in productivity across countries that we observe. Two assumptions provide the empirical basis for this argument. The first is that the returns to human capital are concave, so that with higher levels of human capital the return falls,

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[1] We continue with the Cobb-Douglas form for two reasons. The first is to maintain comparability across the bulk of the macro approach to this subject. The second is that extensive investigation of issues of functional form for the Ghana data, and African firm-level data more generally, have shown the Cobb-Douglas form to be remarkably robust.

and the second is the assumption that the Mincerian returns to education are the same across countries. These assumptions ensure that as human capital expands the return falls so the net effect on underlying productivity of any increase in supply is mitigated. Studies, such as Hall and Jones (1999), that impose a common function $\phi(E_{it})$ do not allow for the empirical investigation of these issues. In the next section we estimate the returns to education in the firm and do not restrict these to be concave or common between countries. There is now growing evidence that concavity does not describe the returns to human capital in poor countries, particularly those in Africa. In fact there is little evidence of any return to human capital for those at the level of education below secondary which is the level for the bulk of the labour force. If this is correct then it opens up the possibility that the return on human capital may be far higher in South Korea than Ghana. The question posed here is whether the data can support a sufficiently large differential to shift up the production function by the scale required to explain differences in productivity across the two countries.

In estimating such production functions issues of functional form are crucial. Two of those issues, which have featured prominently in the literature, have been the use of gross-output or value-added specifications and the use of the Cobb-Douglas as a special case of more general functional forms. Research by Basu and Fernald (1995) shows that adopting a value-added production function can yield misleading results if there is imperfect competition or increasing returns to scale. We therefore propose to adopt a gross output specification and test whether important information is lost when a value-added specification is used. We extend the value-added specification in equation [1] by the inclusion of raw material inputs (M_{it}) and indirect costs (I_{it}) and we are now explicit as to the potential importance of time invariant unobservables in the fixed effects (μ_i):

[6] $$Y_{it} = K_{it}^{\alpha} M_{it}^{m} I_{it}^{i} (A_{it} H_{it})^{\beta} e^{\mu_i} e^{u_{it}}$$

We obtain an equation that includes observable human capital by similar assumptions to those already made:

[7] $$LnY_{it} = \alpha LnK_{it} + mLnM_{it} + iLnI_{it} + \beta\phi(E_{it}) + \beta LnL_{it} + \mu_i + u_{it}$$

From which we obtain the basic specification for this paper:

[8] $$\begin{aligned} LnY_{it} = {} & \alpha LnK_{it} + mLnM_{it} + iLnI_{it} + \beta(\delta_1 E_{it} + \delta_2 E_{it}^2) \\ & + \beta LnL_{it} + \mu_i + u_{it} \end{aligned}$$

In this gross output production function we need measures for five inputs: physical capital, *K*, raw material inputs, *M*, indirect inputs, *I* , years of education, *E* , and labour, *L*. The empirical challenge is to measure these variables in a way that ensures cross-country comparability and allows us to address the issues of endogeneity and the role of unobservables which have dominated attempts to estimate this relationship empirically as reviewed in Tybout (2000) .

Using equation [8] we can identify differences in returns to scale, skills and technology. Constant returns to scale imply that $\beta = (1-\alpha-i-m)$. Differences in skills are captured, in part, by allowing for variation in the measure of human capital which is the years of education (*E*) and, in part, by seeking to identify the returns on human capital across the firms which are a function of (δ_1, δ_2). In this paper we mean by technology the way in which firms combine inputs to produce output, sometimes referred to as the 'blueprints' of production used by the firm. If the 'blueprints' used by firms across these countries differ this will result in the parameters ($\alpha, i, m, \delta_1, \delta_2$) differing. As we are allowing the parameters on education to vary across the countries this aspect of technology acts to shift up the production function. In fact, in this specification, human capital acts just like any other factor which is assumed to affect the underlying TFP of the firm.

As we wish to compare our micro estimates of productivity differences with those from the macro literature we note that we can give an interpretation of how value-added will grow if the correct specification is a gross output production function. By definition:

[9] $$V_{it} = Y_{it} - IM_{it} \text{ and } dV_{it} = dY_{it} - dIM_{it}$$

where for exposition purposes we have merged raw materials and indirect costs into IM_{it}. Denoting shares by s_{im} we have $IM_{it} = s_{im}Y_{it}$ so we can write:

$$V_{it} = Y_{it} - s_{im}Y_{it} = (1-s_{im})Y_{it}$$

[10] $$\frac{dV_{it}}{V_{it}} = \frac{dY_{it} - dIM_{it}}{Y_{it} - IM_{it}} = \frac{1}{(1-s_{im})}\frac{dY_{it}}{Y_t} - \frac{1}{(1-s_{im})}\frac{IM_{it}}{Y_{it}}\frac{dIM_{it}}{IM_{it}} = \frac{1}{(1-s_{im})}\frac{dY_{it}}{Y_t} - \frac{s_{im}}{(1-s_{im})}\frac{dIM_{it}}{IM_{it}}$$

$$\frac{dV_{it}}{V_{it}} = \frac{1}{(1-s_{im})}[\frac{dY_{it}}{Y_t} - s_{im}\frac{dIM_{it}}{IM_{it}}]$$

If gross output and inputs are growing at the same rate then value-added will also be growing at that rate. Basu and Fernald (1995, pp172ff) discuss the biases that can arise if the value-added specification is used, here we note that we can interpret a move from the gross output specification in [8] to a value-added one in terms of such growth rates:

[11] $$\frac{dV_{it}}{V_{it}} = \frac{1}{(1-s_{im})}[\alpha\frac{dK_{it}}{K_t} - \beta\frac{dL_{it}}{L_{it}} + \beta(\delta_1 dE_{it} + \delta_2 dE_{it}^2)]$$

We will use this specification in a comparison of the results from our micro analysis with the work using macro GDP data. We turn now to establish how productivity measures differ across the firms in South Korea and Ghana.

3 Productivity in Ghanaian and South Korean Firms

The data used for the cross-country comparison are unbalanced panels of 863 South Korean manufacturing firms observed for 3 years and 312 Ghanaian manufacturing firms observed for up to 12 years. Both data sets were collected in a similar manner by interviews with firm management. The Ghana data cover the period 1991-2002 and the Korean data the period 1996-98. Söderbom and Teal (2004) use the Ghana data over the period from 1991 to 1997 and the present study extends the data set but retains the definitions used in that paper. The South Korean data are described in Hallward-Driemeier et al (2001).

The key data problem we face is making outputs and inputs comparable both across firms within a country and across countries. We do this in three stages. First we construct the variables so the definitions are consistent across countries. In the second we deflate the values of outputs and inputs by firm specific domestic prices to render them comparable within the country. We finally covert them to international prices by means of the purchasing power parity price indices available from the PENN World Tables, Heston et al (2001). The result is a series of comparable values which should enable us to compare productivity across the manufacturing sectors of South Korea and Ghana.[2]

For both Ghana and Korea we have firm level price deflators for output and some of the inputs. We have used the primary data from the surveys to obtain measures of outputs and inputs classified as raw material inputs and "other inputs" which are primarily indirect costs (electricity, other energy and rent). We have firm level deflators for both output and raw material inputs but not for indirect costs. We proceeded by deflating output and raw material prices by these firm-level deflators and then converting these values to PPP numbers by using the PPP deflator for the base year.[3] For indirect costs, where no appropriate firm-level deflator was available, we have used the PPP consumption deflator for each year. These deflators render the data comparable over time within the country and, as they are firm based, ensure that the variables measure changes in real quantities (at least for output and raw materials) and not higher revenues or lower costs associated with market power.

In order to establish how much of this labour productivity differential can be explained by factor intensity we also need to impute a value to the capital stock for each firm in each country. For the South Korean firms, we take the firm-level reported value of the nominal capital stock for each year and deflate it using the annual PPP investment deflator. For the Ghanaian firms, as we have a longer panel available and due to concerns about capital valuation in this less developed market, we accumulate the deflated value of the investment series and assume a depreciation rate rather than using the reported values of the capital stock.

[2] Details of the calculations are given in the Appendix. In the text we focus on the key decisions made to render the data comparable across the two countries.

[3] In cases where these firm level price indices were not available they were assumed to be equal to the average of firms in the same manufacturing sub-sector.

Having made the data comparable within the country we then proceed to render it comparable across countries by means of country level PPP deflators for the base year which is 1991 for Ghana and 1996 for Korea. We use the GDP PPP deflator for output, the investment PPP deflator for capital and the consumption PPP deflator for materials, the latter being the same as that already used for the indirect costs. It is at this stage that problems of comparability are most pronounced. Given our interest in comparing TFP, not only across firms within a country but also across firms in such very different countries as Ghana and South Korea, any error in this deflation will appear in the TFP difference. Our defense is that the PPP exchange rates represent our best estimate of price level differences across countries.

Finally we turn to how the human capital augmented labour variable has been created. The measure of labour input is weekly hours worked. For Ghana we use the firm-level data on employment and average hours worked. In South Korea we do not have firm-level data on hours worked, and so we use the subsector (ISIC 2-digit) averages from the ILO. Our human capital measure is the average number of years of education of workers in the firm. For Ghana, where we have time variation, the measure is obtained from labour market surveys carried out at the same time as the firm surveys. These labour market surveys contain information on the years of education by occupation of the worker and we have aggregated up the individual level data to a firm basis using the occupational structure of the firm. For South Korea we have the proportion of the workforce that has completed various levels of education and from this we impute an implied average by assuming that workers finish the level of reported education. This measure however has no time variation. In order to make the measures comparable we remove the time variation in the Ghanaian data by taking an average for each firm.

Table 1 presents the results of these calculations. The median output per employee is 20 times higher in Korea than Ghana firms while the differential in terms of median value-added per employee is nearly 40 times. The differences in capital per worker are larger still, with the medians differing by a factor of nearly 50 times. Quite clearly the firms are performing very differently and using quite different factor intensities. How much of these differences can our production function capture?

4 Estimating technology and the returns to skills

In order to allow both technology and underlying efficiency to differ across the firms we proceed by seeking a separate estimate of equation [6] for both Ghana and South Korea. As we have sought to make the units of measurement comparable across the countries we can then ask how large is any difference in TFP. The estimation of such production functions involves a number of econometric problems which, despite having been the subject of a considerable literature, are still under active discussion. Endogeneity resulting from unobserved time-varying factors being correlated with inputs, encompassing both omitted variable bias and measurement error, has generally been seen as the critical issue for the estimation of production functions. There have been four main techniques in the literature to overcome endogeneity problems: instrumental variable estimation (IV), fixed effects estimators (FE), structural identification and generalised method of moments (GMM) panel data estimators. The difficulty in finding suitable instrumental variables, the bias in FE estimators from measurement error and multicollinearity problems with structural identification (Ackerberg and Caves (2005)) lead to the GMM approach being the primary one adopted in this paper, although we also present some results for other methods.

The GMM approach uses the autocorrelation structure of the residuals to obtain a set of moment conditions. In the language of instrumental variable estimation, lags of levels are used as instruments for first-differences and lags of first-differences are used as instruments for levels. The particular set of moment conditions that is available is dependent upon the autocorrelation structure of the residuals. The GMM estimator and the diagnostic tests are implemented using the xtabond2 command (Roodman 2005) in the STATA statistical package. The autocorrelation structure is determined through the use of the Arellano-Bond (1991) *m* statistics. These test the null of no autocorrelation of the specified order and determine how many lags need to be taken in order to arrive at valid moment conditions.

The overall validity of the moment conditions (or, equivalently, of the instruments) is validated through the use of the Sargan test with the null hypothesis that the instruments are valid (ie exogenous). The original version of this estimator consisted solely of an equation in first-differences with appropriately lagged levels as instruments (Arellano and Bond 1991). In the case of highly persistent data, lagged variables in levels are likely to be weak instruments for contemporaneous differences, potentially giving rise to finite sample bias and poor precision of the estimates. To address such problems a system generalised method of moments (GMM) estimator was developed, (Blundell and Bond (1998), Blundell and Bond (2000), Blundell, Bond and Windmeijer (2000) and Windmeijer (2000)). Within this framework lagged levels are used as instruments for contemporaneous differences and lagged differences as instruments for contemporaneous levels. This resulting system GMM estimator nests the original difference GMM estimator and so a difference-in-Sargan test can be used to check the validity of the additional instruments used in the levels equation.

The first-differencing operation not only removes unobserved firm-specific effects but also time-invariant explanatory variables. This presents a problem if the effects of time-invariant variables are of interest as the instrumenting procedure described above is only available for endogenous variables that are time-varying. In our equations, this means that we are able to use the moment conditions to instrument capital, labour, materials and indirect costs but not education. In Table 2 we assume that education is exogenous, however, due to concern that it may be correlated with unobservables, we undertake some more detailed analysis of alternative instrument sets in Section 5 in order to check that this assumption is not material to our conclusions.

The basic result in this paper is presented in Table 2 which compares the Ghanaian and South Korean firms using identical specifications which impose, after testing, constant returns to scale. Consider first the OLS results. We would expect these to be biased by the presence of unobservables, such as management ability and measurement error. The coefficients on variables that are positively correlated with unobservables will be biased upwards while those that are negatively correlated will be biased downwards. We use two approaches to investigate whether the OLS coefficients are biased by endogeneity. Firstly, we implement a fixed-effects estimator. This removes firm-specific time-invariant unobservables from the data, and hence also removes any bias they may cause. As is typical in production function estimation, likely due to measurement error, the coefficients in the unrestricted fixed effects estimator are implausibly low but become reasonable with constant returns imposed. As constant returns to scale are not rejected in any of the other specifications we are comfortable imposing this restriction for the fixed effects estimator. The system GMM panel data estimator allows for the autoregressive structure of productivity shocks and measurement error to be unrestricted, and, further, allows both of the former and the fixed effect to be freely correlated with input choices. Thus, from an endogeneity perspective, the GMM results should be unbiased if the instruments are valid and if education is exogenous. We test for autocorrelation of varying degree and lag the instruments sufficiently given the results of these tests. The subsequent Sargan test does not reject the validity of the instruments even when we implement the correction proposed by Bowsher (2002) to correct for the known tendency of this test to under-reject.[4]

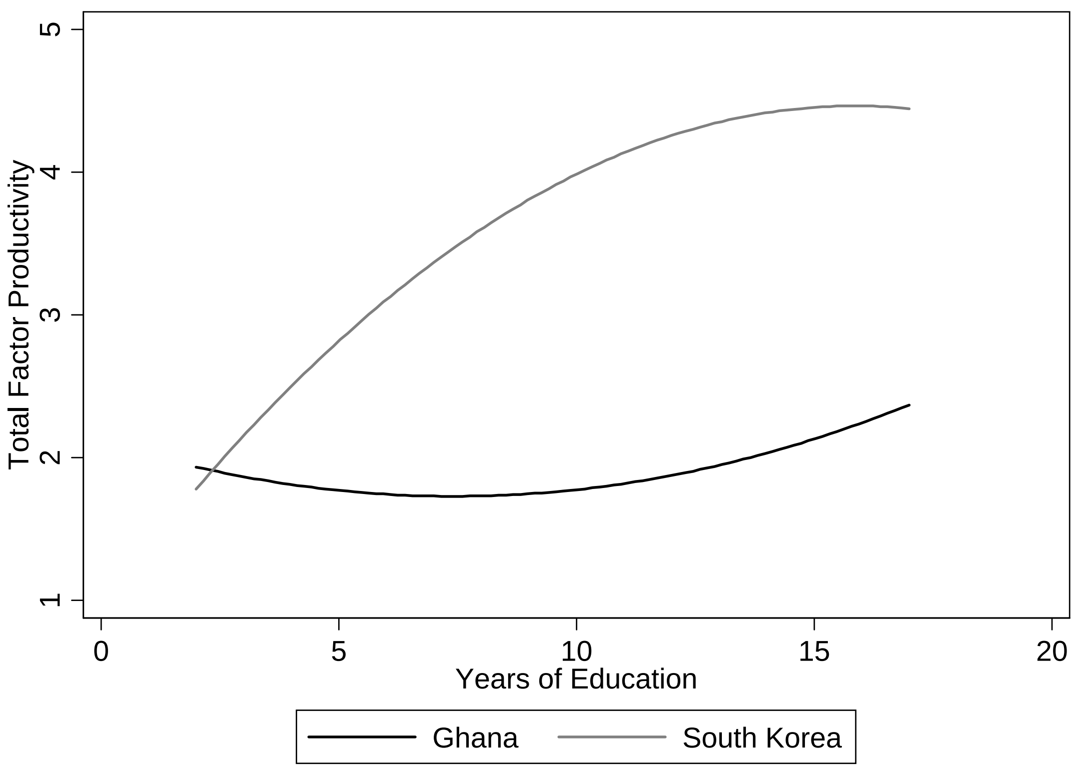
Our main result focuses on the differing impact of education on firm output in the two countries. The quadratic functional form allows for the possibility that the shape and the magnitude of returns differ. The returns implied by Table 2 in Ghana are small and convex while those in South Korea are larger and concave. Note that while the South Korean coefficients are not individually significant, the joint null hypothesis that the linear and quadratic terms are equal to zero is easily rejected. Taking the first derivative of the quadratic and evaluating at the sample mean gives an implied marginal rate of return of 3% in Ghana and 10% in South Korea.[5] The returns to education functions are plotted in Figure 1. Average returns to education can also be calculated. As there are no observations at very low levels of education we are wary of

[4] The Difference-in-Sargan test, which tests for the validity of the additional lagged differences instruments in the levels equation, while not reported, also does not reject the instruments.

[5] Calculated as -0.094+(2*0.006*10)=0.026 for Ghana and 0.444-(2*0.014*12)=0.108 for South Korea.

extrapolating the quadratic too far. As such, the average rate of return is calculated assuming that the total returns to education are reflected in the quadratic from 3 years to the maximum

Figure 1 TFP and Education



observed in each country. That is, we take $\phi(3)$ (rather than $\phi(0)$) as an estimate of the intercept of the returns to education function. This calculation yields average rates of return on years of education of 14.5% per annum in South Korea and 1.8% per annum in Ghana.[6]

Compared to the other specifications, the constant term in the fixed effect equation is much higher for South Korea and virtually identical for Ghana. This implies that time-invariant factors, which includes education in our model, are important for explaining productivity in South Korea but not in Ghana. In Table 3 we use a logarithmic function in Equation 3 as a way of imposing concavity in the returns, while still allowing returns to differ. This compares to the approach in Hall and Jones (1999) where concavity was imposed with a common rate of return. Based upon the quadratic specification we expect that this functional form will be rejected for Ghana but not for South Korea which the empirical results confirm. The Ghanaian coefficient is

[6] Calculated as (ϕ (15)- ϕ(3))/15=(0.015+0.249)/15=0.018 for Ghana and (ϕ(16)- ϕ(3))/16=(3.52-1.20)/16=0.145 for South Korea.

not significantly different from zero, while the greater structure imposed means that the South Korean coefficient is now highly significant. The implied rate of return at the mean is 11%. Black and Lynch (1996) estimate a very similar specification for US firms and find a point estimate on the log of education of 0.86 for manufacturing firms, midway between our estimates for Ghana and South Korea.

As we have chosen units so that they are comparable across countries we can clearly interpret the constant term in the regression as the differences in TFP across the countries. In Table 3, with concavity imposed, the constant terms are almost equal. In Table 4 education is not included in the production function and the logarithmic TFP difference between Ghana and South Korea is 2.4. Using the implied rates of return calculated from Table 2 the difference that can be attributable to education is $e^{(0.10*12-0.03*10)} = 2.4$. This is exactly the implied difference in TFP in Table 4 where we exclude education for the production function. The estimation of value-added Equation 5 is presented in Table 5 and we would anticipate that these coefficients will be biased if the gross output is the correct specification. The logarithmic difference in TFP when education is excluded in 3.8, compared to the 2.4 in the corresponding gross output specification in Table 4. Even allowing for a quadratic education effect, as in columns 1 and 3, the implied logarithmic TFP difference at E=10 is 3.43. We consider below the implied coefficients on value-added from the gross output specification of Table 2.

Any difference in point estimates on the inputs can be interpreted as differences in technology across the countries. Table 2 shows that there is a clear difference in technology with Ghanaian firms having a substantially higher material elasticity of output and lower capital and labour elasticities. This, together with the results already presented for the value-added specification, suggests that a gross output specification of the production function is to be preferred. The share of inputs comprised of intermediate inputs is much higher in Ghana than in South Korea - 85% as opposed to just under 50%. This means that, for every unit of output produced, Ghanaian firms are spending relatively more on raw materials and relatively less on payments to workers and capital owners. In understanding how firms in Ghana may evolve to resemble those in South Korea considering input technology appears to be important.

5 Some robustness checks

Before turning to interpreting our main result we consider possible problems with the regressions reported in Tables 2 and 3. The first is the possibility that the instrumentation procedure we have used is not valid. The second is that, while we are using a far more narrowly defined set of commodities than comparisons using macro data, there is substantial aggregation bias and this is affecting our results. Finally we consider the possibility that issues of functional form are of importance.

The fixed effects estimator will remove any endogeneity bias if the relevant unobservables are time-invariant. The GMM estimator uses lags of levels and first-differences of inputs as instruments to additionally control for time varying productivity shocks. While our diagnostics support the use of these instruments, there are other sets of instruments that can be exploited. In particular, we need to address concern that education may be correlated with unobservables to such an extent that assuming it is exogenous severely biases our results. The results of these checks are presented in columns 1, 2 and 3 of Table 6. The key conclusion from these robustness checks is that the instrumenting procedure is not changing our view about the shape and relative magnitude of the return to education coefficients.

Column 1 exploits the time variation in the education measure available for Ghana to instrument for E in the system GMM style.[7] This is not only a check of our instrumenting procedure, but also that the averaging of the education measure carried out for Ghana has not biased our results. The implied return on education in Ghana is low and insignificant when education is assumed to be endogenous, as it was in Table 2. Thus, at least in Ghana, the exogeneity assumption is not causing significant bias in our estimate of the returns to education. If one believes that the correlation between education and unobservables is similar in the two countries then this implies that the exogenenity assumption is also unproblematic for South Korea. Alternatively, one may believe that the types of unobservable factors important in South Korea are fundamentally different. If this is true and these are causing the South Korean estimate on E to be substantially biased upwards then this merely reinforces our conclusion. Skills are used in very different ways across the two economies – it is just that the factors that are associated with this different use of skills are unobserved.

In columns 2 and 3 of Table 6 we again assume that education is endogenous and use firm-level wages and an index of material prices as additional instruments (in South Korea there are separate indices for imported and non-imported materials). These alternative instruments are accepted by the Sargan tests, although with lower p-values. The coefficients on inputs are of a very similar pattern and magnitude to those in Table 2. The only substantive difference is that the coefficient on E in South Korea is higher (although so is its standard error). Given that education is generally considered to be potentially positively correlated with firm-level unobservables this suggests that, if anything, our estimate of the returns to education in South Korea presented in Table 2 is an underestimate.

[7] Instrumenting both the linear and quadratic terms in education caused some instability in the estimates so only the linear term, capturing the average returns to education, is included.

As a further check on the likelihood that the exogeneity assumption on education is material we extracted the time-varying component of the error term (ie residual minus the fixed effect) from the fixed effect regressions of Table 2. Recall that education is effectively excluded from these regressions as our measure is time-invariant. Using this error as the dependent variable an OLS regression with education (linear and quadratic terms) as independent variables produced small and highly insignificant coefficients. This suggests that education is not correlated with time-varying unobserved productivity shocks.[8]

We have been considering firms at the level of the aggregate manufacturing sector. While most firms are from sub-sectors common to both countries, it may be that the aggregation of sub-sectors is causing substantial bias. In order to check for this we restricted the analysis to include only those firms in the textiles and garments sector. The results are presented in columns 4 and 5 of Table 6 and show the same pattern of coefficients across countries within this common sub-sector. While the restricted sample has resulted in some less precise identification we see that the return to education is low and convex in Ghana and high and concave in South Korea and that the coefficient on materials is much higher in Ghana and the coefficient on labour inputs correspondingly lower. That these results hold even when restricted to a sector that is common between the countries, and is known to be highly globalised, gives us confidence that the differences we observe are not a result of differing sectoral composition in the samples.

Finally our analysis could be generalised by considering different functional forms. Table 3 presents the estimations when education is included as a logarithmic effect rather than a quadratic effect and, again, the same pattern of coefficients is observed. While other work using these data sets has concluded that the Cobb-Douglas functional form is appropriate (Söderbom and Teal (2004), Hallward-Dreimier et al (2002)) it may be that this is too restrictive a specification. The Cobb-Douglas functional form is a first-order logarithmic Taylor series approximation with the translog being the second-order extension by including interaction terms between inputs. The translog production function has the problem that it is not globally concave and that output elasticities differ by input combination making interpretation more cumbersome. However, estimating the translog and evaluating the elasticities implied in Table 2 at the sample mean for each country did not change our conclusions. In fact, as the Cobb-Douglas is nested within the translog, finding difference in the Cobb-Douglas is a stronger conclusion than finding it in the translog.[9]

6 Why does productivity differ?

[8] The correlation between the error term and education is less than 0.01 in absolute value in both countries.

[9] The exception to this would be if there was a common translog production function and Ghanian and South Korean firms are merely using different factor combinations (say due to differences in factor prices).

In Table 1 we showed the very large differences in labour productivity between South Korean and Ghanaian firms. These differences greatly exceed those implied by the macro data which underlie the calculations of Hall and Jones (1999). Table 7 shows the results from their paper for Ghana and South Korea where both are ranked relative to the US. This macro data suggests that labour productivity differs by a factor of 7 times, while large this is much smaller than the differences in value-added per worker of 40 times in Table 1. In the Hall and Jones decomposition shown in the Table by far the most important factor in explaining this productivity differential is TFP which is nearly 3 times higher in South Korea than Ghana. This figure is close to the differences we observe for differences in TFP across the firms in the two countries for the gross output specification where we do not control for education. The key to our result is that the returns to education differ across the two countries by very large amounts.

There has been an extensive discussion in the literature on the returns to education that the rises in the returns to education that can be found for some periods in the US and UK is due to skill biased technical change, see Card and DiNardo (2002) for a recent review of this literature. Our data suggest that the much higher levels of capital per employee, which reflect in part the far greater sophistication of the technology used in South Korea relative to that in Ghana, is associated with much higher returns to that education. Such a result is wholly consistent with those who have argued that rises in the return to education within developed countries can be explained by skill-biased technical progress in those economies. Our results are also consistent with work in developing countries which finds a convex return to education based on individual labour market data, see Bigsten et al (2000) for Africa and Kingdon and Unni (2001) and Duraisamy (2002) for India.

While the differences in labour productivity are very large, once we allow the technology across the countries to differ and control for education, but allowing returns to differ, there is no statistically significant difference in TFP between the firms in the two countries. While there must remain doubts as to how well our deflation procedure has rendered outputs and inputs comparable across countries the difference with the results from macro analysis appears remarkable. In order to link our micro production functions with the macro analysis we must convert our gross output specification to value-added to ensure comparability of our labour productivity measures.

If we use equation [11] above and apply the GMM parameter estimates from Table 2 we can calculate the implied value-added equation. We obtain for Ghana:

$$\frac{dV_{it}}{V_{it}} = \frac{1}{(1-0.82)}[0.05\frac{dK_{it}}{K_t} - (1-0.05-0.82)\frac{dL_{it}}{L_{it}} + 0.018dE_{it}]$$

$$\frac{dV_{it}}{V_{it}} = 0.30\frac{dK_{it}}{K_t} - 0.70\frac{dL_{it}}{L_{it}} + 0.10dE_{it};$$

and for Korea:,

$$\frac{dV_{it}}{V_{it}} = \frac{1}{(1-0.51)}[0.16\frac{dK_{it}}{K_t} - (1-0.16-0.51)\frac{dL_{it}}{L_{it}} + 0.145dE_{it}]$$

$$\frac{dV_{it}}{V_{it}} = 0.30\frac{dK_{it}}{K_t} - 0.70\frac{dL_{it}}{L_{it}} + 0.295dE_{it}.$$

The rather remarkable result is that in value-added terms both equations produce the same point estimates on the capital and labour inputs. We can thus return to our original production function, indeed with the same points estimates on capital as are assumed by Hall and Jones (1999), and write the above equation in levels as:

$$V_{it} = K_{it}^{\alpha}(A_{it}H_{ih})^{(1-\alpha)}$$

We are now in a position to answer our question as to why South Korean firms produce so much more output per worker than Ghanaian ones. Setting A_{it} equal to the differences in the returns to human capital we have:

$$\frac{V_{it}}{L_{it}} = \left[\frac{K_{it}}{L_{it}}\right]^{\alpha} e^{\delta h}$$

For Ghana and Korea we have, respectively,

$$\frac{V_{it}}{L_{it}} = [1.3]^{0.3} e^{0.100\cdot 10} = 2.94 \qquad \text{and} \qquad \frac{V_{it}}{L_{it}} = [61]^{0.3} e^{0.295\cdot 12} = 118.3$$

Producing a 40 fold difference in the value-added per employee across the firms in the two countries and consistent with the observed differences in medians in Table 1.

The mean years of education do not differ markedly between the two countries, 10 and 12 years respectively. What does differ markedly is the shape of the (firm-level) returns to education function and the average return. In Ghana this is a very flat convex function, while in South Korea it is a concave function. The returns in Ghana are much lower: even with the convexity returns do not reach 10% until the 15th year of education, while the average return over the observed range is 3 per cent. A South Korean firm will be most productive when its workers have had 15.8 years of education, while Ghanaian firms only begin experiencing positive returns to education once their workers have more than 7 years of education.

This difference in the coefficients of education is a part of what we have termed a 'technology difference' between the two countries. If you give the workers in a South Korean firm an extra year of education, the firm can harness this to increase output. Give the same increase to workers in a Ghanaian firm and output barely changes. An implication of this is that giving Ghanaian workers more education is not going to help as the key difference lies in the way that educated workers are used within the firm.

Figure 2 Value-added and capital per worker expressed in 1996$PPP

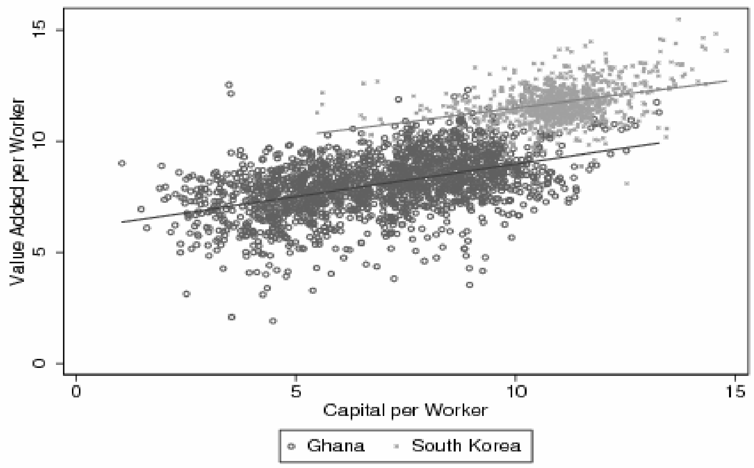


Figure 2 is a scatterplot of value-added per worker versus capital per worker for the two samples of firms. At the micro level this recreates what has been observed in the macro data. Ghanaian firms form a distinct cluster from their South Korean counterparts and the significant level gap in value-added per worker is significant and is not closed by increases in capital intensity. While the macro data appeals to differences in TFP, our micro analysis suggests this gap can be explained by differences in technology: chiefly by differences in the returns to education but, also, partly by differences in the physical input coefficients.

7 Conclusions

This paper set out to investigate why output per worker is so much higher for firms in South Korea than for firms in Ghana. Two firm level datasets were constructed where care was taken to ensure consistent variable definitions and appropriate deflators. Production was modeled using a gross-output production function where we allowed for the input coefficients and the Mincerian returns to education to differ across countries. Endogeneity was controlled for using a variety of methods, including through the use of the system GMM estimator.

There is an extensive macro literature seeking to explain the very large differences in output per worker observed across countries. The general conclusion from this literature has been that these differences cannot be explained by observable inputs, in particular by human and physical capital, and that the key is to be found in the determinants of TFP. A similar conclusion has been drawn from analysis of micro data which seeks to identify factors that affect firm level TFP. Our paper points to the possible role that observable differences in technology may play. The higher output per worker in South Korean firms can be accounted for through a combination of factor intensity, technological differences and, most importantly, differences in the shape of the relationship between human capital and productivity across the countries. It is these, not TFP, which explain why South Korean firms have a labour productivity 40 times higher than those in Ghana.

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Data Appendix

The data used are a balanced panel of 863 South Korean manufacturing firms observed for 3 years and an unbalanced panel of 312 Ghanaian manufacturing firms observed for 12 years. The Ghanaian data was collected in a series of interviews with firm management and cover the period 1991-2002. Along with the survey questionnaire, this data is publicly available from the Centre for the Study of African Economics at the University of Oxford. The data set (including definitions and variable construction) is that used in Soderbom and Teal (2004) with the addition of the more recent survey rounds. The data used to estimate the production function are the value of physical capital stocks, number of employee-hours (number of employees multiplied by average weekly hours), expenditure on materials and other inputs (mostly electricity, other energy and rented land, buildings and equipment) and average firm worker years of education. There are also price indexes for output and material inputs used to convert the variables into real 1991 domestic currency prices. Gross output is measured as total sales, adjusted by changes in inventories.

The South Korean data were collected in face-to-face interviews covering 1996-1998, and are described in Hallward-Driemeier (2001). The data and the survey questionnaire are publicly available from the World Bank. Output is calculated as sales plus the change in inventories, with other production variables being value of physical capital stock, number of employees and expenditure on materials, electricity, other energy and rented land, equipment and buildings. These final three inputs are aggregated into a single factor so as to be comparable with the Ghanaian data. Again, there are firm-level price indexes for output and material inputs used to convert the data into real 1996 domestic currency. Where these price indexes were not available the sectoral averages were used. The variables in the South Korean dataset were transformed into ratios and truncated before they were made publicly available, and the recovery of the levels of the variables from these transformations will have introduced some additional measurement error into the data. Firms with more than 500 employees or within the top 5% for asset value were truncated and so these have been dropped from the sample. This means that the South Korean sample contains more small firms than the true firm population which, if anything, should reduce any apparent differences with the smaller Ghanaian firms. Average hours worked by sector were obtained from the ILO and used in the construction of the employee-hour variable.

PPP deflators from PWT 6.1 were used to convert the real domestic quantities in each country into international quantities. The PPP investment deflator was used for the capital stock, the consumption deflator for indirect and material inputs, and the GDP deflator for output.

Variable	Ghana		South Korea	
	Mean	Median	Mean	Median
Output (Y)	2,753	179	40,992	16,210
	(10,003)		(74,530)	
Capital (K)	1,180	21	21,771	4,798
	(5,729)		(66,583)	
Employment (L)	73	22	122	84
	(155)		(125)	
Indirect inputs (I)	651	15	648	216
	(2,677)		(1,890)	
Materials (M)	1,183	82	14,005	4,719
	(4,969)		(27,630)	
Y/L	20.3	9.8	290.5	192.8
	(35.3)		(355.4)	
K/L	7.77	1.32	115	61
	(29.4)		(207)	
I/L	3.21	0.85	4.50	2.32
	(7.31)		(8.41)	
M/L	10.0	4.1	98	60
	(20.0)		(132)	
V/L	7.1	3.1	188	116
	(16.7)		(303)	
Hours	46	45	46	46
	(9)		(2)	
Education(yrs)	10.0	10.1	12.7	12.7
	(2.5)		(1.2)	
Firms	257		358	
Observations	1884		919	

Table 1: Descriptive Statistics for variables used in estimation. The monetary values are express as '000 1996 $PPP. Standard errors are in parenthesis.

	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 2: 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.

	Ghana		Korea	
	OLS	GMM	OLS	GMM
lnK	0.039	0.059	0.111	0.165
	[0.012]**	[0.020]**	[0.028]**	[0.084]*
lnH	0.116	0.131	0.414	0.346
	[0.013]**	[0.024]**	[0.037]**	[0.091]**
lnE	0.102	0.107	1.51	1.291
	[0.069]	[0.085]	[0.284]**	[0.294]**
lnI	0.189	0.152	0.224	0.149
	[0.018]**	[0.024]**	[0.030]**	[0.061]*
lnM	0.655	0.659	0.251	0.34
	[0.023]**	[0.027]**	[0.037]**	[0.077]**
Constant	1.547	1.527	1.258	1.098
	[0.178]**	[0.203]**	[0.642]	[0.702]
Observations	1880	1880	918	918
Firms		254		357
CRS	0.049	0.907	0.296	0.156
AR1		0.000		0.488
AR2		0.000		
AR3		0.462		
Sargan		144.314		15.362
Sargan df		145		17
Sargan p		0.500		0.569

Table 3: Production functions in 1996 $PPP for Ghana and South Korea with logarithmic education. Other notes as for Table 2.

	Ghana		Korea	
	OLS	GMM	OLS	GMM
lnK	0.043	0.063	0.124	0.183
	[0.011]**	[0.020]**	[0.028]**	[0.084]*
lnH	0.114	0.128	0.381	0.322
	[0.013]**	[0.023]**	[0.034]**	[0.091]**
lnI	0.191	0.156	0.226	0.142
	[0.018]**	[0.024]**	[0.031]**	[0.063]*
lnM	0.652	0.654	0.269	0.353
	[0.023]**	[0.028]**	[0.035]**	[0.080]**
Constant	1.776	1.770	4.860	4.178
	[0.087]**	[0.106]**	[0.234]**	[0.651]**
Obs	1884	1884	919	919
Firms		257		358
CRS	0.033	0.960	0.103	0.179
AR1		0.000		0.506
AR2		0.000		
AR3		0.462		
Sargan		143.677		14.297
Sargan df		145		17
Sargan p		0.515		0.646

Table 4: Production functions in 1996 $PPP for Ghana and South Korea excluding education. Other notes as for Table 2.

	Ghana		Korea	
	GMM	GMM	GMM	GMM
lnK	0.371	0.414	0.194	0.221
	[0.084]**	[0.067]**	[0.140]	[0.138]
lnH	0.629	0.586	0.806	0.779
	[0.084]**	[0.067]**	[0.140]**	[0.138]**
E	-0.523		0.538	
	[0.145]**		[0.380]	
E^2	0.028		-0.015	
	[0.009]**		[0.015]	
Constant	5.190	2.724	2.311	6.558
	[0.660]**	[0.250]**	[2.331]	[1.010]**
Observations	1774	1778	907	908
Firms	253	256	354	355
AR1	0.000	0.000	0.120	0.123
AR2	0.000	0.000		
AR3	0.839	0.877		
Sargan	82.342	80.754	5.798	3.854
Sargan df	73	73	9	9
Sargan p	0.213	0.250	0.760	0.921

Table 5: Value-added production functions in 1996 $PPP for Ghana and South Korea. Other notes as for Table 2.

	E_t	GMM-IV		Textiles and Apparrel	
	Ghana	Ghana	Korea	Ghana	Korea
lnK	0.057	0.050	0.190	0.061	0.060
	[0.018]**	[0.020]*	[0.095]*	[0.022]**	[0.084]
lnL	0.126	0.123	0.296	0.136	0.296
	[0.023]**	[0.024]**	[0.122]*	[0.034]**	[0.211]
lnI	0.164	0.180	0.177	0.124	0.370
	[0.022]**	[0.026]**	[0.066]**	[0.036]**	[0.132]**
lnM	0.653	0.648	0.336	0.680	0.275
	[0.027]**	[0.028]**	[0.084]**	[0.036]**	[0.118]*
E	0.008	0.067	0.230	-0.031	1.776
	[0.007]	[0.033]*	[0.156]	[0.593]	[0.808]*
E^2				0.003	-0.063
				[0.031]	[0.033]
Constant	1.694	1.132	1.185	1.738	-7.435
	[0.123]**	[0.323]**	[1.562]	[2.840]	[4.949]
Observations	1842	1851	876	419	190
Firms	254	252	345	54	77
Educ				0.586	0.000
AR1	0.000	0.000	0.520	0.001	0.352
AR2	0.000	0.000		0.033	
AR3	0.366	0.420		0.019	
Sargan	180.919	143.709	19.228	35.666	15.803
Sargan df	181	146	19	145	17
Sargan p	0.488	0.538	0.442	1.000	0.538

Table 6: Robustness Checks. All estimators are system GMM as in Table 2 with additional instruments as specified. Column 1 uses the time-varying measures of education for Ghana to check that the averaging by firm done earlier for consistency is not causing bias. Columns 2 and 3 assume that education is completely endogenous and uses wages and material input prices as additional instruments. Columns 4 and 5 repeat the regressions of Table 2 solely for those firms in the Textiles and Garments sector. Other notes as for Table 2.

Country	*Y/L* Labour Productivity	$(K/Y)^{\alpha/(1-\alpha)}$ Capital to Output	*H/L* Human Capital per worker	*A* Total Factor Productivity
Ghana	0.052	0.567	0.464	0.198
Korea	0.380	0.880	0.761	0.568

Table 7 Comparisons based on Hall and Jones (1999).