Are African Manufacturing Firms Really Inefficient? Evidence from Firm-Level Panel Data[$]

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Abstract: Three dimensions of the performance of firms in Ghana's manufacturing sector are investigated in this paper: their technology and the importance of technical and allocative efficiency. We show that the diversity of factor choices is not due to a non-homothetic technology. Observable skills are not quantitatively important as determinants of productivity. Technical inefficiency is not lower in firms with foreign ownership or older firms and its dispersion across firms is similar to that found in other economies. Large firms face far higher relative labour costs than small firms. If these factor market distortions could be removed substantial gains thorough improvements in allocative efficiency would be possible.

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1. Introduction

Three issues have been prominent in policy discussions of the problems facing firms in developing countries. One has been that technology differences may be important in explaining factor choices across firms of differing size, Pack (1976, 1982). Small firms have come to be identified with more labour intensive technologies so that promoting small scale enterprises is seen as a means of creating jobs. A second issue has been that firms in developing countries lack the technical capacity to perform well. “Without an increase in proficiency, the responsiveness of output to even the best designed structural adjustment program is likely to be limited. Prices are one-half of a scissor, the other being technical skill”, Pack (1993, p. 1). The third has been that larger firms are more capital intensive than smaller ones and that such factor choices are inappropriate for the factor endowment of poor countries. A comprehensive discussion of these issues in the context of Indian industrial policy can be found in Little, Mazumdar and Page (1987).

While much of the analysis of efficiency and size has used macro or sectoral data there are now numerous studies based on plant-level data sets, Pitt and Lee (1981), Martin and Page (1983), Corbo and de Melo (1986), Chen and Tang (1987), Tybout (1991), Tybout and Westbrook (1995) Clerides, Lach and Tybout (1998), and Lundvall and Battese (2000). Two of these studies use data for sub-Saharan Africa where it has been argued that the problems of technical inefficiency are likely to be most important. In this paper we propose to investigate these issues of technology choice, the importance of skills, both observed and unobserved, and the relative importance of technical and allocative inefficiency, drawing on a seven year panel of plant-level data from Ghana’s manufacturing sector.

A wide range of technology choices is made across firms of differing size in our sample. We propose to investigate four of the possible explanations for this finding suggested by Little, Mazumdar and Page (1987). The first is that factor prices vary depending on the size of the firm, the second is non-homothetic technology, the third is that firms in different sectors, or of differing size, or age, may operate with different levels of technology and the fourth is that firms may not pursue the objective of maximising profits. The existence of panel data enables us to extend work in this area for sub-Saharan Africa in several respects. The ability to estimate a production function with fixed effects ensures that skills which are unobserved, but time-invariant, do not bias the parameter estimates. We can then ask if these unobserved aspects of the technology, measured through the fixed effects, do depend on ownership or firm age two factors which have been widely argued to measure access to better managerial skills and the importance of firm learning. Thus in measuring technical inefficiency the existence of panel data means that we do not need to assume, as in the case with cross-section data, a distribution for the residual to identify the component of inefficiency.

Our data contains measures of the human capital in the firm. We can therefore address directly the Pack contention that such skills play an important role in the efficiency with which firms perform. We also propose to assess the potential importance of allocative inefficiency across firms of differing size. The contention that large firms use too capital intensive a technology is essentially an argument that factor market distortions prevent large firms responding to the same factor prices as smaller firms. The finding of a correlation between factor choices and firm size may, of course, reflect differences in underlying technology related to firm size or sector, not differences in technology choice based on different prices. Distinguishing between these alternative hypotheses is one of our objectives.

The relationship between technology and efficiency measures is discussed in the next section. In Section 3 we set out the production function and in Section 4 provide an overview of the data. The results of estimating both value-added and gross output production functions are presented in Section 5. Their implications for technology choice and skills are discussed in Section 6. In Sections 7 and 8 the importance of technical and allocative efficiency is investigated. A final section concludes.

2. Technology, Factor Choice and Efficiency

The analysis in this paper will be based on standard production theory, assuming that the relationship between inputs and output can be approximated by a production function that is known to the firm. We write the production function in general notation as

$$Y_{it} = A_{it}F(Z_{it}) \tag{1}$$

where Y_{it} is the level of output, A_{it} is total factor productivity (TFP) and Z_{it} is an n order vector of inputs, where we assume that $F:\Re_{+}^{n} \rightarrow \Re_{+}$ is continuous, strictly increasing and quasi-concave.[1] The latter two assumptions are readily testable and we shall come back to this in the empirical analysis.

Technology and Factor Choice

Factor demand is intimately linked to the firm's technology and factor prices. Empirical studies based on firm-level data, both from developed and developing countries, typically report substantial variation in factor intensities across firms which thus suggests that there is significant heterogeneity in technology and/or factor prices across firms.

The first two of the explanations offered by Little, Mazumdar and Page (1987) are illustrated in Figure 1, where we consider the case of two inputs, capital (K) and labour (L). In the top panel of the figure we keep technology constant and let the relative price of capital decrease with size, so factor prices vary with firm size and large firms choose more capital per employee than small ones. The bottom panel illustrates the second explanation, with constant factor prices but with non-homothetic technology so that the marginal rate of technical substitution decreases in (absolute) size for a given capital-labour ratio. Again large firms have higher capital-labour ratios, but in this case this is caused by the nature of the technology rather than by heterogeneous factor prices. The third explanation, heterogeneous technology, can be thought of as one aspect of a general measurement problem. Like most authors we measure the physical capital stock in (real) monetary units, so that different vintages of capital yielding differences in productivity should be reflected in differences in the value of the capital. Imperfect valuation of different vintages, not unlikely in practice, would therefore introduce measurement errors in the observed capital stock. The fourth potential explanation, that firms do not maximise profits, is accommodated in the analysis provided that deviations from profit maximisation can be modelled by means of a random term.

Technical Efficiency

Equation (1) represents the 'frontier', or 'best practice', production function in that it defines the maximum output attainable for firm *i* at time *t*, given the technology A(it) and the input set Z(it). Firms that use A(it) and Z(it) inefficiently, however, will not achieve their maximum potential output. The ratio between actual and potential output is conventionally defined as the level of *technical inefficiency*, where firms that use A(it) and Z(it) efficiently will have an inefficiency score of unity, and inefficient firms will have scores in the (0, 1) interval.[2] There has been a continuing development of methods over the past 50 years to compute inefficiency scores, with the two principal methods being stochastic frontiers, which is based on

[1] These are standard assumptions: continuity ensures that small changes in the vector of inputs lead to small changes in output; F[ ] being strictly increasing ensures that employing strictly more of every input yields strictly more output; and quasi-concavity implies that the isoquants are convex towards the origin (see e.g. Jehle and Reny, 1998, p. 220).

[2] Modern efficiency measurement begins with Farrell (1957).

econometric methods, and data envelopment analysis (DEA), relying on mathematical programming. While DEA is attractive in that it does not require any parametric assumptions or assumptions about the functional relationship between inputs and output, a significant disadvantage of this procedure is that the computed inefficiency scores are very sensitive to measurement errors, either in output or the input variables. Therefore, in our view, DEA is not very well suited to survey data sets and will not be used in this paper.[3] Stochastic frontiers accommodate statistical noise in the dependent variable by means of introducing a residual, while typically treating inefficiency as a random parameter. A general class of such models, which specialises to several in the literature, is presented in Battese and Coelli (1992), another general form is that proposed by Battese and Coelli (1993). One unattractive feature of these random effects models is that the inefficiency term typically is assumed to be uncorrelated with the explanatory variables in the frontier production function. If the inefficiency terms are in fact correlated with firm attributes, the estimated parameters and the inefficiency scores from such models will be biased (Tybout, 1992).

Given that both the inefficiency term and the residual are unobservable, there are substantive identification issues that need to be addressed. With cross-section data it is not possible to separate the residual from inefficiency without making parametric assumptions about the distribution of the residual and the inefficiency term, which is unattractive.[4] If panel data is available, and if it is reasonable to assume that inefficiency is approximately constant over the time-span during which the firm is observed, then we can model inefficiency as a time invariant firm specific effect. This is the route we will take in this paper. Contrary to most papers in the area we shall make no assumptions about the distribution of inefficiency, and we shall also allow the inefficiency term to be freely correlated with the arguments of the production function. Defining the inefficiency term as $U_i = \exp(-u_i)$ and the residual as ε_{it} we rewrite the production function as

$$Y_{it} = A_{it} F(Z_{it}) \cdot U_i \cdot e^{\varepsilon_{it}} . \tag{2}$$

In the empirical analysis we will allow for correlation between ε_{it} and the arguments of F, caused by, for instance, measurement errors of the kind discussed above. We will return to this issue below.

Allocative Efficiency

The second dimension of efficiency with which we are concerned is that of *allocative efficiency*. In production theory, allocative efficiency conventionally reflects the ability of the firm to use optimal factor combinations, given their respective prices. That is, in the context of the graphs in Figure 1, the firm would be allocatively inefficient if it were to choose a point on the isoquant at which the isocost line is not tangential. Failure to maximise profits, as discussed above, will therefore manifest itself as allocative inefficiency. A related but distinct form of allocative efficiency occurs when as a result of price distortions, which may be due, for example, to non-competitive factor markets, differential taxation on firms of differing size or the payment of efficiency wages, firms of differing size select different factor

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[3] Lundvall (1999) uses both DEA and stochastic frontiers on Kenyan survey data, and reports an average inefficiency score of 0.38 based on DEA and 0.77 based on a stochastic frontier. The substantially lower score yielded by DEA is consistent with presence of measurement errors in the dependent variable.

[4] Even if one is prepared to make such distributional assumptions, measuring technical inefficiency with cross-section data is difficult. As all inputs determining output which are omitted from the production function will give rise to the appearance of technical inefficiency clearly measured technical inefficiency may simply reflect how imperfect are the measures of inputs rather than how poorly managers transform inputs into outputs, Tybout (1992).

combinations.[5] We have already referred to the view common in the development literature that larger firms are more capital intensive than smaller ones and that such factor choices are inappropriate for the factor endowment of poor countries. This definition of allocative inefficiency is thus intimately linked to the first explanation offered by Little, Mazumdar and Page (1987) as to why factor ratios may vary across firms.

We propose to investigate the potential importance of such allocative inefficiency by examining how large are the differences in technology choice that can be attributed to differences in factor prices. Our data enables us to provide an estimate of the cost reduction possible if factor price distortions could be removed.

3 The Production Function

In order to translate (2) into an expression suitable for econometric analysis, we need to adopt an explicit functional form of the production function F which provides a reasonably close approximation of the real technology. One flexible form which has been used extensively in studies estimating cost and production functions is the second-order transcendental logarithmic ('translog') production function (Christensen et al, 1971; Berndt and Christensen, 1972), which we write as

$$\ln Y_{it} = \sum_j \beta_j \ln X_{jit} + 1/2 \sum_k \sum_m \beta_{km} \ln X_{kit} \ln X_{mit}\,, \qquad \beta_{rs} = \beta_{sr} \text{ for all } s,\, r, \tag{3}$$

where X_j is the j:th input in the production process, j=1,2,..., J, and β denotes parameters to be estimated. The translog specification is attractive because it nests or approximates a number of popular models in the literature, and for our purposes it is especially useful because output and substitution elasticities are allowed to vary with the levels of the inputs, hence homotheticity is not imposed.[6] The following shows three key parameter restrictions on (3) which we shall test for in the empirical analysis:

$\sum_k \beta_{km} = 0 \quad (m = 1,2,\ldots,J)$ (homotheticity);

(4a)

$\sum_k \beta_{km} = 0 \quad (m = 1,2,\ldots,J)$, (4b)

$\sum_k \beta_k = 1$ (constant returns to scale);

$\beta_{km} = 0 \quad (k = 1,2,\ldots,J;\ m = 1,2,\ldots,J)$ (Cobb-Douglas form). (4c)

In our empirical analysis we will use two definitions of the dependent variable in the production function, namely gross output and value-added. Value-added production functions appear to be more common in the literature, however 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 will therefore present results for both value-added and gross output production functions in the results below. In the output production function we use four inputs: labour, denoted L, physical capital, K, raw material inputs, M, and indirect inputs, I. Because value-added is defined as output minus costs for raw material and indirect inputs, we use only labour and capital as inputs in the value-added specification.

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[5] In particular, notice that allocative inefficiency defined like this is not the result of optimisation errors made by the firm.

[6] The cost of such flexibility is that it is necessary to test for monotonicity and quasi-concavity at each data point. It is a common result in the empirical literature to find that not all observations comply with these conditions. Typically in such cases the production function is nevertheless considered well-behaved '…if the conditions are met for a sufficient number of the observed levels of inputs and outputs…' (Little, Mazumdar and Page, 1987, p. 162).

To allow explicitly for the role of human capital in the production process, we follow Hall and Jones (1999) and Bils and Klenow (2000) and augment the logarithmic production function (3) with αh_{it}, where α is a parameter vector to be estimated and h_{it} is a human capital vector consisting of average level of education, tenure, age of employees in the firm, and age squared. We expect positive coefficients on education and tenure, and an inverse u-shaped effect of age. Finally, we add a vector of time dummies, D, measuring common shocks to the firms over time, with the associated vector of coefficients, δ. Hence we arrive at the following empirical specification:

$$\ln Y_{it} = \sum_j \beta_j \ln X_{jit} + 1/2 \sum_k \sum_m \beta_{km} \ln X_{kit} \ln X_{mit} + \alpha h_{it} + \mu_i + \delta \cdot D_t + \varepsilon_{it} . \qquad (5)$$

In estimating (5) we need to deal with the fact that the explanatory variables are likely to be correlated both with the equation error and with the firm specific effect. For instance, the regressors will be correlated with the equation error if managers alter their inputs in response to contemporaneous shocks to output. Failure to allow for such simultaneity is expected to yield an upward bias in the estimated coefficients. It is also likely that explanatory variables are measured with error, as discussed above, which, if ignored, is expected to cause a downward bias in the estimated coefficients. To address these problems we will use an instrumental variables approach, where we exploit the panel dimension of the data and use lagged values of the explanatory variables as instruments.[7] As this approach rules out using the within transformation to wipe out the firm effects (see e.g. Griliches and Hausman, 1986), we will take first differences. However, recent research has shown that lagged levels will be weak instruments for contemporaneous differences when data are highly persistent, potentially giving rise to finite sample bias and poor precision of the estimates (Blundell and Bond, 1998).[8] Therefore we follow Blundell and Bond and combine the differenced equation with a levels equation to form a system generalised method of moments (GMM) estimator, which uses lagged levels as instruments for contemporaneous differences and lagged differences as instruments for contemporaneous levels.[9] Naturally, the legitimacy of this procedure hinges on the instruments being valid, which will be tested for. We provide a brief discussion of the system GMM estimator in Appendix 1.

4 Data

This study uses panel data on manufacturing firms in Ghana, collected in face-to-face interviews with the firms' management during five survey rounds in the 1990s. The data is annual and covers the 1991 to 1997 period. At the same time as the firms were surveyed a sample of workers and apprentices was chosen from each firm designed to cover the full range of personnel employed by the firms. The objective was to have up to 10 workers and 10 apprentices from each firm where firm size allowed. As a result of this survey design it is possible to use the responses from workers in the firm to create firm-level averages of worker

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[7] Clearly, this is one important benefit of panel data. In the case where the researcher has cross-section data only, purging explanatory variables from simultaneity typically requires extraneous information of the kind often unavailable in practice.

[8] In highly persistent time series, lagged levels will be poor instruments for contemporaneous differences but lagged differences may still be good instruments for contemporaneous levels. For instance if X follows a random walk, $X_t = X_{t-1} + \varepsilon_t$, implying $\Delta X_t = \varepsilon_t$, then X_{t-1} will be uncorrelated with ΔX_t, but ΔX_t will nevertheless be correlated with X_t. Blundell and Bond (1998) present results from a Monte Carlo experiment indicating that the system GMM estimator performs substantially better than the standard differenced GMM when the data are highly persistent.

[9] Recent papers following this approach are Blundell and Bond (2000), Blundell, Bond and Windmeijer (2000) and Windmeijer (2000).

characteristics. During the course of the surveys a sub-set of 143 firms have provided data on the components of value-added and sufficient information that the capital stock, employment and the human capital stock of the firm could be calculated for at least three consecutive years.[10] In the regression we lag the physical capital stock by one year so the maximum period over which we can observe the firms is six years. The resulting unbalanced panel contains 656 observations. The three major additions to the primary data are the derivation of physical stocks from investment flows, the calculation of firm-level human capital stocks based on worker information and the construction of firm specific price indices for outputs and material inputs. These prices, which differ for outputs and inputs, are used to deflate all output and inputs into constant price (1991) domestic currency prices. All references in the text and tables refer to these deflated values for output, input and physical capital stock. The average size of firm, measured by employment across the seven rounds of the data, is 67 employees and the standard deviation is 113, so the range of enterprises covered by the survey is very large. Firms range in size from 2 to 841 employees.

Table 1 presents descriptive statistics for the key variables in our empirical analysis. Four size categories are identified: the micro which is firms with less than 6 employees, small those with from 6 to 30, medium those with from 31 to 99, and large those with 100, or more, employees. The upper panel of the table (under the heading 'Conditional Means') shows mean values for the monetary and human capital variables, purged of sectoral and time effects as explained in the notes to the table. We purge the variables from time effects to ensure that the results are not driven by changes in the sample composition during the course of the surveys. The fact, shown in Table 1, that the capital labour ratio differs substantially across firm of differing size when the data is purged of sectoral effects is important for establishing that it is not differences in technology related to sector which explains the dispersion. For all the variables shown in the upper part of the table the mean values increase monotonically over the size range, indicating that large firms have higher labour productivity and capital intensity, and more skilled workers. For the log of output, value-added and capital, per employee, the increases are substantial, corresponding to about 150 per cent, 230 per cent and 900 per cent, respectively, in levels. These descriptive statistics confirm that a wide range of technology choices are made by firms in our sample. In the following sections we propose to investigate the reasons for these choices.

5 Estimates of Value-added and Gross Output Production Functions

In addressing the issue of technology and productivity, two issues are central to our investigation: whether technology is non-homothetic and how human capital impacts on productivity performance. In Table 2 we report various production function results, based on OLS and the within estimator. We begin by looking at the left part of the table, where we model value-added.

The OLS results for the translog model, Column [1], clearly suggest that the data complies very well with the regularity conditions, as both quasi-concavity and monotonicity is fulfilled at each observation.[11] There is no strong evidence of non-homotheticity or variable

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[10] To obtain a measure of the human capital stock available to the firm it was necessary to merge the worker with firm level information. In aggregating from the worker to the firm level we used weights to ensure that we can move from individual data to firm based averages. To do this we weighted the human capital variables by the proportion of workers in a given occupational class within the firm. Eight common occupational groups across the rounds of the survey were identified. These occupational categories for the worker level data are matched with the occupational categories given in the firm level data. A data appendix explaining the details of this procedure is available on request from the authors.

[11] Monotonicity requires that each input has a positive marginal product, and quasi-concavity requires that the bordered Hessian matrix of first and second partial derivatives of the production function are negative

returns to scale, and the Cobb-Douglas specification can easily be accepted given the translog functional form. Column [3] reports OLS results for the Cobb-Douglas specification, and the results are very similar to those obtained from the translog model. The estimated coefficient on employment is 0.89, and that on physical capital is 0.18, and both are significant at the 1 per cent level. The human capital coefficients all have the anticipated signs, however only the age effect, which is a quadratic, is significant.

These OLS results will be biased if, which seems likely, the explanatory variables are correlated with the unobserved firm specific effects. When we introduce controls for firm fixed effects, however, the production function disintegrates, Columns [2] and [4]. Implausibly, physical capital now appears to have a negative, although insignificant, effect on value-added, and monotonicity is violated at each observation. The standard explanation why controlling for fixed effects in the production function tends to give unsatisfactory results is that the differencing procedure exacerbates the bias caused by measurement errors in the explanatory variables, Griliches and Mairesse (1997).[12] To address this issue we will utilise the panel nature of the data to search for valid instruments. We will come back to this shortly.

We now turn to the right-hand part of the table, where we model gross output. Column [5] reports OLS results for the translog model. Again we cannot reject homotheticity and there is no evidence for variable returns to scale, however it now seems we should decisively reject the simpler Cobb-Douglas model in favour of the translog specification. Only 44 per cent of the observations fulfil quasi-concavity and 69 per cent comply with monotonicity, which is not satisfactory. Introducing controls for fixed effects, Column [6], only makes matters worse in this respect, presumably for the reasons discussed above. Estimating the Cobb-Douglas model using OLS, Column [7], gives positive and significant coefficients on all inputs. We can compare the point estimates to those obtained in the value-added model [3] if we assume that the cost of raw materials and indirect inputs is a constant fraction of output. Under this assumption, the coefficient on employment of 0.14 in the output model translates into 0.82 in a value-added equation, while the capital coefficient of 0.03 corresponds to 0.18 in a value-added equation. Hence there is no evidence that the two models give radically different results. As for the human capital variables, we now obtain a significant but small coefficient on education, and a significant inverse u-shaped age effect.

None of the models reported in Table 2 will yield consistent results in the presence of endogeneity and measurement errors, so we need to probe the data further before we can draw conclusions about the properties of the production function. In Table 3 we report system GMM results controlling for fixed effects and using lags of explanatory variables in levels as instruments for contemporaneous differences, and lags of the explanatory variables expressed in first differences as instruments for contemporaneous levels. All results in this table are two-step GMM estimates, where the *t*-statistics are based on robust, finite sample corrected standard errors (see Windmeijer, 2000).[13] Column [1] summarises the translog results for the

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semi-definite. In the translog specification the marginal products and the partial derivatives depend both on the values of the inputs and on the estimated parameters, and we therefore need to investigate if monotonicity and quasi-concavity holds at each data point.

[12] If the sample is 'large' and the regression has only one regressor, measurement errors alone cannot be the reason why differencing changes the sign of the estimated coefficient (see Deaton, 1997, p. 109). This simple rule does not hold, however, if there are several explanatory variables or the sample size is finite.

[13] It is well known that the asymptotic standard errors in two-step GMM estimators can be severely downward biased in finite samples (e.g. Arellano and Bond, 1991). As a consequence, researchers often draw inference based on one-step GMM estimators, which are less efficient than the two-step estimators. However, Windmeijer (2000) shows how the asymptotic two-step standard errors can be corrected when the sample size is finite. Monte Carlo evidence reported by Bond and Windmeijer (2001) indicates that this procedure yields a much more reliable basis for inference than relying on the asymptotic standard errors.

value-added specification, and because we can easily accept the Cobb-Douglas model within the translog framework, we focus on the Cobb-Douglas results reported in Column [2]. The results appear to be reasonable. The estimated employment coefficient is 0.73, that on capital is 0.31, and both coefficients are significant at the 1 per cent level. There is no evidence of variable returns to scale, or, by implication of the Cobb-Douglas specification, non-homotheticity. Among the human capital variables only age has a significant impact on productivity. The point estimates on the age terms indicates an inverse *u*-shaped effect of workers' age on productivity, which peaks approximately at the age of 32.

Column [3] in Table 3 reports system GMM estimates of the output translog production function. Like for all other models previously reported, there is no evidence for non-homotheticity or variable returns to scale. Further, in contrast to the OLS and within models reported in Table 2 for the output specification, we can now comfortably accept the Cobb-Douglas specification, reported in Column [4], as a result of using instrumental variable techniques. We consequently focus on the results in Column [4]. The estimated coefficient on employment is equal to 0.17, and significant at the 1 per cent level, which can be compared with 0.14 in the OLS model and 0.10 in the within specification. More dramatically, the estimated capital coefficient is 0.09, hence substantially higher than in the OLS (0.03) and within (-0.06) specifications, and significant at the 5 per cent level. The input elasticities sum to 1.00, i.e. constant returns to scale. The coefficient on tenure is now significant at the 10 per cent level, although its magnitude is very small. As in all other models, we obtain a quadratic age effect, indicating that productivity increases with the average age of the workforce up until the age of 32 years, and then decreases. The education coefficient is insignificant.

6 Technology and Skills

In summary the Cobb-Douglas models in Table 3 appear to be very well specified. The Sargan-Hansen tests indicate that the instruments are valid, and the fact that the capital coefficient is higher than in the OLS and within specifications is consistent with this variable being measured with error. For all estimators we can easily accept the hypothesis that technology is homothetic. The ease with which firms can substitute one input for another does not vary with firm size thus suggesting that technology is *not* the reason why we observe differing factor intensities over the size range. There is no evidence for variable returns to scale, except in some of the within regressions which we believe to be biased downwards for reasons already discussed.

The OLS results suggest that education of the workforce may have a significant impact on productivity, which squares with previous studies based on the early waves of the Ghana data (Jones, 2001; Bigsten et al, 2000). However, our results show that this effect vanishes once controls for firm fixed effects and endogeneity are introduced. We have also tested for complementarity between physical capital and human capital, but in no case did we find a significant coefficient on any of the relevant interaction terms. We have attempted to address the possibility that firms may operate with different levels of technology by using econometric methods that yield consistent results in the presence of what is essentially a measurement problem. By including controls for workers' education, age and tenure, we have also acknowledged that differences in human capital may map into productivity differences. We find that measured skills are not an important determinant of productivity.

7 Technical Inefficiency

In reviewing studies which measure the dispersion of productivity in developing countries, Tybout (2000, p. 25) argues that "they are not very informative. Most of them are based on outdated methodologies. With a few exceptions they rely on cross-sectional data, and hence must infer efficiency dispersion from the skewness of the production function residuals.

Further, because they measure output as real revenue, they misattribute cross-plant mark-up differences to productivity dispersion. Finally, for lack of data, they typically attribute high productivity with superior performance, ignoring many of the costs that firms incur to enhance their technical efficiency". Our analysis has addressed each of these concerns. We have used recently developed econometric techniques that enable us to control for simultaneity (e.g. in the form of measurement errors in inputs or feedback from output to factor choices) and unobserved heterogeneity (in the form of firm fixed effects, freely correlated with the inputs). We have used panel rather than cross-section data and we have used firm-level information on input and output prices to construct firm specific deflators. Finally, we have used detailed data on human capital to directly measure skills. What are the implications of these procedures for measures of technical efficiency?

We estimate the fixed effects based on the output production function reported in Column [4], Table 3, and use these as our measures of technical inefficiency.[14] To be able to compare the dispersion of technical inefficiency with previous studies, we normalize so that the efficiency index, te_i, is bounded in the (0 ,1] interval: $te_i = e^{-(\hat{\mu}_{\max} - \hat{\mu}_i)}$, where $\hat{\mu}_{\max}$ is the sample maximum of the estimated fixed effects, and $\hat{\mu}_i$ is the estimated fixed effect for firm *i*. Hence an efficiency score equal to 1 indicates efficiency or 'frontier' technology, and scores less than 1 indicate inefficiency. Figure 2 shows the distribution of this efficiency index. The sample mean of this fairly skewed distribution is 0.53. However, as can be seen from the graph, the fairly low average inefficiency score is partly caused by a few outliers, and eliminating the five largest fixed effects from the sample would increase the average inefficiency score to 0.60.

Tybout (2000, Tables 2 and 3) provides an extensive summary of inefficiency studies for developing countries with a comparison, from Caves et al. (1992), of efficiency measures from Australia, Japan, Korea, UK and US. The latter report country averages of the efficiency index ranging between 0.67 and 0.70. As Tybout notes there is little evidence that the dispersion of efficiency in developing countries is very different from that in developed. The average across all the studies cited for developing countries is 0.6, identical to the finding above and only slightly below that for OECD countries.

In Table 4 we regress the fixed effects estimates on time invariant variables, to see if we can detect any systematic variation in efficiency across sectors, ownership structures, locations and other firm characteristics. Few of the regressors have strong explanatory power. With the metal sector as the omitted category, we find inefficiency to be about 24 percentage points lower in the wood sector, 11 percentage points lower in the food sector and 13 percentage points higher in the textiles sector. These effects are individually significant at the 10 per cent level or better, and all the sector dummies are jointly significant at the 1 per cent level. Neither firm age nor ownership are associated with significant efficiency differentials. The R-squared from the regression indicates that our regressors manage to explain only 16 per cent of the variation in the fixed effects.

8 Allocative Inefficiency

In the last section we showed that the dispersion of output in the Ghanaian firms differed little from those observed in other economies. There is no empirical support for the notion that these firms are atypically technically inefficient. We have also showed that the technology is homothetic so it is not differences in technology which explain differences in factor choice with firm size. We know from Table 1 that the capital labour ratio does increase with size. In

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[14] We obtain estimates of the fixed effects by regressing the levels residuals on firm dummies, where the resulting coefficients on the firm dummies are the estimated fixed effects.

this section we explore the potential size of allocative inefficiency if these differences do reflect differences in factor prices. Söderbom and Teal (2001) use this data to argue that evidence from earnings function are consistent with such an hypothesis.

Figure 3 shows the relationship between the capital labour ratio and firm size by means of the results from a Nadaraya-Watson kernel regression of the form $\ln(K/L) = f(\ln L)$ + error, where the dependent variable has been purged of time and sectoral effects (see notes to Table 1). Using a nonparametric approach in this context is attractive as it puts little restriction on the shape of the function f (.). The figure shows the estimated regression line and pointwise 95% confidence intervals, obtained through bootstrapping. While the regression as expected shows that the capital labour ratio increases with size, the pattern appears to be non-linear. The positive correlation between size and capital intensity is strongest for firms between 10 and 200 employees, outside this range the regression function is relatively flat and the confidence interval wide. Within the (10, 200) range, the average slope of the regression line is about unity, indicating that a 1 per cent increase in the labour force is associated with a 1 per cent increase in the capital labour ratio.

Based on this regression we use the predicted values of $\ln(K/L)$, and calculate the implied capital stock values for given levels of employment. This yields the expansion path of factor combinations. We plot this in Figure 4 along with isoquants based on a Cobb-Douglas value-added production function with a capital coefficient of 0.3 and a labour coefficient of 0.7, thus very similar to the regression reported in Column [2], Table 3. Clearly the expansion path bends off sharply towards the capital axis, and because technology is homothetic we know that the slope of the isoquants will be steeper for higher capital labour ratios. The figure shows that firms with 200 employees have on average 6 times higher relative labour to capital costs than firms with 21 employees. In their analysis of the wages in the Ghanaian manufacturing sector Söderbom and Teal (2001) report that the earnings-size elasticity is about 0.20, which would predict 80 per cent higher labour costs in firms with 200 employees than in firms with 10 employees.[15] This would imply that the capital prices differ between the two size categories by a factor of between 3 to 4 times. It will be noted that differences in capital costs across firms of differing size are far larger than labour costs.

While the cost of capital to the firms cannot be directly observed we can infer it from the production function and the assumption that the marginal product of capital is equal to the firm specific cost of capital. From Table 3 Column [4] we note that the marginal product of capital =0.09x(Y/K). From Table 1 we note that [using ln(Y/K) =ln(Y/L)-ln(K/L)] Y/K for a large firm is 0.96 and for a micro firm is 4.2, numbers which imply a rise in the cost of capital from small to large firms of about 4 times, from 10 to 38 per cent.

Figure 4 shows the enormous dispersion of factor choice which these differences in factor prices imply. If the large firm (ie one with 200 employees) output were produced using small firm (ie one with 20 employees) factor proportions the amount of labour would be 70 per cent higher while the capital required would be less than a third that actually used. What are the implications of these differences for cost reduction if it were possible for large firms to face the labour costs of small firms or, equivalently, for small firms to face the capital costs of large firms? The implication of our findings is that unit costs would fall by about 30 per cent. The capital labour ratio that would result would be approximately half that of the large firm but some 4 times higher than that currently chosen by small firms.[16] The extent of the welfare

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[15] Söderbom and Teal (2001) control for human capital and fixed effects in their estimation of an earnings function which gives the 0.2 point estimate on the log of employment

[16] These figures can be simply derived from the Cobb-Douglas production function set out in the notes to Figure 4 and the implied unit cost equation which is $r((w/r)\cdot 0.3/0.7)^{0.7} + w((r/w)\cdot 0.7/0.3)^{0.3}$, where r is the rental price of capital and w is the wage rate. We normalise the price at 60 and assume labour costs for small firms of

gain from this cost fall would depend on the shape of the demand function. However, that both substantial cost reductions, and a far more efficient use of capital, is possible than is currently the case is the clear implication of our findings.

9 Summary and conclusions

The view that firms in Africa are inefficient has been widespread. In this paper we have used panel data to investigate both technical and allocative inefficiency. We have shown that a very simple functional form, the Cobb-Douglas, adequately represents the technology choices made by firms where firm size ranges from less than 5 to over 200. The implication of the acceptance of the Cobb-Douglas function form is that the technology is homothetic so that differences if factor choices over firms of differing size is not a reflection of differences in technology. We have shown that the dispersion in technical efficiency over firms in our sample is similar to that found in other countries. There is no evidence that firms in Africa are particularly inefficient in this sense. We have also investigated the possible roles of both observable human capital, and the unobserved skills as proxied by the fixed effects, as determinants of efficiency. Observable skills are not quantitatively important as determinants of productivity. We have investigated if either ownership, or firm age, are correlated with the unobserved components of skills, as measured by the fixed effect. Neither significantly affects this measure of the efficiency with which firms operate. In contrast we have found evidence that there is substantial allocative inefficiency. Large firms facing higher relative labour costs than smaller firms use a much more capital intensive technology and operate with costs 30 per cent higher than those which would occur if factor prices were common across firms of differing size. While that might be the case has been part of the folk wisdom of development economics for a very long time our data has enabled us to document the size of this effect.

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30 and for large firms of 54, while capital costs respectively are 10 and 38 per cent. The capital labour ratio for small firms is 0.3 and for large is 2.3 [see Figure 4]. Unit cost is 60 by normalisation for both technologies. Using large firm capital costs and small firms labour costs the unit cost is 40 and the capital labour ratio is 1.3. Clearly these figures are intended to be indicative of orders of magnitude and are not to be interpreted as exact.

References

Arellano, M., Bond, S., 1991. Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. Review of Economic Studies 58, 277-297.

Basu, S., Fernald, J. G., 1995. Are apparent productive spillovers a figment of specification error? Journal of Monetary Economics 36, 165-188.

Battese, G.E., Coelli, T.J., 1992. Frontier production functions, technical efficiency and panel data: with application to paddy farmers in India. Journal of Productivity Analysis 3, 159-169.

Battese, G.E., Coelli, T.J., 1993. A stochastic frontier production function incorporating a model of technical inefficiency effects. Working Papers in Econometrics and Applied Statistics 69. Department of Econometrics, University of New England, Armidale.

Berndt, E., Christensen, L., 1972. The translog function and the substitution of equipment, structures, and labor in U.S. manufacturing, 1929-1968. Journal of Econometrics 1, 81-114.

Bigsten, A., Collier, P, Dercon, S., Gauthier, B., Fafchamps, M., Gunning, J.W., Isaksson, A., Oduro, A., Oostendorp, R., Pattillo, C., Söderbom, M., Teal, F., Zeufack, A., Appleton, S., 2000. Rates of return on physical and human capital in Africa's manufacturing sector. Economic Development and Cultural Change 48, 801-827.

Bils, M., Klenow P., 2000. Does schooling cause growth? American Economic Review 90, 1160-1183.

Blundell R., Bond, S., 1998. Initial conditions and moment restrictions in dynamic panel data models. Journal of Econometrics 87, 115-143.

Blundell R., Bond, S., 2000. GMM estimation with persistent panel data: an application to production functions. Econometric Reviews 19, 321-340.

Blundell, R., Bond, S., Windmeijer, F., 2000. Estimation in dynamic panel data models: improving on the performance of the standard GMM estimator, in: Baltagi, B. (Ed.), Advances in Econometrics, Vol. 15: Nonstationary Panels, Panel Cointegration and Dynamic Panels. JAI Elsevier Science, Amsterdam.

Bond, S., Windmeijer, F., 2001. Finite sample inference for GMM estimators in linear panel data models. Mimeo. The Institute for Fiscal Studies, London.

Caves, R., Bailey, S.D., et al., 1992. Industrial efficiency in six nations. MIT Press, Cambridge and London.

Chen, T., Tang D., 1987. Comparing technical efficiency between import-substitution-oriented and export-oriented foreign firms in a developing economy. Journal of Development Economics 26, 277-289.

Christensen, L. R., Jorgensen, D. W., Lau, L. J., 1971. Transcendental logarithmic production frontiers. The Review of Economics and Statistics 55, 28-45.

Clerides, S.K., Lach, S., and Tybout, J. R., 1998. Is learning by exporting important? Micro-dynamic evidence from Colombia, Mexico and Morocco. Quarterly Journal of Economics 113, 903-947.

Corbo, V., de Melo, J., 1986. Measuring technical efficiency: A comparison of alternative methodologies with census data, in: Dogramaci, A. (Ed.), Measurement Issues and Behavior of Productivity Variables. Kluwer Nijhoff, Boston.

Deaton, A., 1997. The Analysis of Household Surveys: A Microeconometric Approach to Development Policy. Published for the World Bank by The Johns Hopkins University Press, Baltimore and London.

Farrell, M. J., 1957. The measurement of productive efficiency. Journal of the Royal Statistical Society A120, 253-290.

Griliches, Z., Hausman, J.A., 1986. Errors in variables in panel data. Journal of Econometrics 31, 93-118.

Griliches, Z., Mairesse, J., 1997. Production functions: the search for identification, in: Strom, S. (Ed.), Essays in Honour of Ragner Frisch. Econometric Society Monograph Series. Cambridge University Press.

Hall, R. E., Jones, C.I., 1999. Why do some countries produce so much more output per worker than others? Quarterly Journal of Economics 114, 83-116.

Hansen, L. P., 1982. Large Sample Properties of Generalized Method of Moments Estimators. Econometrica 50, 1029-1054.

Jehle, G. A., Reny, P. J., 1998. Advanced Microeconomic Theory. Addison-Wesley, Reading, Massachusetts.

Jones, P., 2001. Are educated workers really more productive? Journal of Development Economics 64, 57-79.

Little, I. M. D., Mazumdar, D., Page Jr, J. M., 1987. Small manufacturing enterprises: A comparative analysis of Indian and other economies. Published for the World Bank by Oxford University Press, Washington.

Lundvall, K., 1999. Essays on Manufacturing Production in a Developing Economy: Kenya 1992-92. Ekonomiska Studier 93. PhD Thesis at Department of Economics, Göteborg University.

Lundvall, K., Battese, G., 2000. Firm size, age and efficiency: evidence from Kenyan manufacturing firms. Journal of Development Studies 36, 146-163.

Martin, J.P., Page Jr., J., 1983. The impact of subsidies on X-efficiency in LDC industry: theory and an empirical test. Review of Economics and Statistics 65, 608-617.

Pack, H., 1976. The substitution of labour for capital in Kenyan manufacturing. Economic Journal 86, 45-58.

Pack, H., 1982. Aggregate implications of factor substitution in industrial processes. Journal of Development Economics 11, 1-38.

Pack, H., 1993. Productivity and industrial development in sub-Saharan Africa. World Development 21, 1-16.

Pitt, M.M., Lee, L. F., 1981. The measurement and sources of technical inefficiency in the Indonesian weaving industry. Journal of Development Economics 9, 43-64.

Söderbom, M., Teal, F., 2001. Firm size and human capital as determinants of productivity and earnings. CSAE Working Paper WPS 2001.9. Centre for the Study of African Economies, Department of Economics, University of Oxford.

Tybout, J. R., 1991. The effects of trade reforms on scale and technical efficiency: new evidence from Chile. Journal of International Economics 31, 231-250.

Tybout, J. R., 1992. Making noisy data sing: Estimating production technologies in developing countries. Journal of Econometrics 53, 25-44.

Tybout, J. R., 2000. Manufacturing firms in developing countries: how well do they do and why? Journal of Economic Literature 38, 11-44.

Tybout, J. R., Westbrook, M. D., 1995. Trade liberalisation and the dimensions of efficiency change in Mexican manufacturing industries. Journal of International Economics 39, 53-78.

Windmeijer, F., 2000. A finite sample correction for the variance of linear two-step GMM estimators. IFS Working Paper 00/19. London: The Institute for Fiscal Studies.

TABLE 1
SUMMARY STATISTICS

	[1] Micro	[2] Small	[3] Medium	[4] Large	[5] All
CONDITIONAL MEANS*					
Log Output per Employee	13.75	13.91	14.08	14.68	14.08
	(0.12)	(0.06)	(0.07)	(0.10)	(0.04)
Log Value-Added per Employee	12.48	12.67	12.92	13.68	12.90
	(0.15)	(0.07)	(0.09)	(0.12)	(0.05)
Log Capital per Employee	12.39	12.48	13.73	14.72	13.22
	(0.19)	(0.09)	(0.12)	(0.16)	(0.06)
Ratio of Value-Added to Output	0.34	0.36	0.38	0.39	0.37
	(0.02)	(0.01)	(0.01)	(0.02)	(0.01)
Average Education in Years	9.58	9.81	10.28	11.27	10.18
	(0.27)	(0.13)	(0.16)	(0.22)	(0.09)
Average Age in Years	26.52	28.69	33.43	35.55	31.02
	(0.78)	(0.38)	(0.47)	(0.64)	(0.26)
Average Tenure in Years	3.38	4.22	6.90	7.21	5.42
	(0.48)	(0.24)	(0.29)	(0.39)	(0.16)
UNCONDITIONAL MEANS					
Firm Age (years)	15.17	14.45	19.28	22.87	17.39
Any Foreign Ownership (proportion)	0.14	0.07	0.23	0.59	0.22
Any State Ownership (proportion)	0.00	0.02	0.09	0.06	0.05
Industry (proportions)					
Food and Bakery	0.32	0.22	0.18	0.25	0.22
Wood	0.00	0.03	0.06	0.29	0.08
Furniture	0.13	0.28	0.27	0.20	0.25
Textiles and Garments	0.33	0.16	0.20	0.00	0.16
Metal and Machinery	0.22	0.31	0.28	0.25	0.28
Location (proportions)					
Accra (capital city)	0.32	0.60	0.63	0.55	0.57
Cape	0.06	0.02	0.03	0.03	0.03
Kumasi	0.49	0.35	0.28	0.13	0.30
Takoradi	0.14	0.03	0.06	0.29	0.10
Number of Observations	72	292	193	119	677
Number of Firms	15	61	40	27	143

Note: The size of the firm is its total number of employees when first observed in the sample, where a micro firm has less than six employees, a small firm has from 6 to 29, a medium firm has from 30 to 99, while a large firm has 100, or more, employees. The figures in ( ) are standard errors. All monetary variables have been deflated using firm-level price indices.

Table notes continue on the next page

Table notes, continued

* These numbers are means that have been purged from time and sectoral effects. The numbers reported in Columns [1]-[4] are predictions from regressions of the variables on sector, time and the size dummies, where the predictions are based on sample means for the sector and time dummies. The numbers reported in the fifth column are predictions from regressions of the variables on sector and time dummies and the level of employment, where we use sample means for the sector, time and employment to compute the predictions.

TABLE 2: OLS AND WITHIN ESTIMATES OF PRODUCTION FUNCTION PARAMETERS

	Dependent variable: log Value-Added				Dependent variable: log Output			
	Translog		Cobb-Douglas		Translog		Cobb-Douglas	
	[1] OLS	[2] Within	[3] OLS	[4] Within	[5] OLS	[6] Within	[7] OLS	[8] Within
MARGINAL EFFECTS(1)								
log Employment	0.84	0.30	0.89	0.34	0.10	0.03	0.14	0.08
	(8.79)**	(1.31)	(9.74)**	(1.59)	(3.33)**	(0.46)	(3.78)**	(1.18)
log Capital	0.20	-0.25	0.18	-0.22	0.02	-0.06	0.03	-0.06
	(3.57)**	(0.65)	(3.43)**	(0.59)	(1.68)$^{+}$	(0.46)	(2.12)*	(0.53)
log Raw Materials					0.72	0.69	0.71	0.65
					(37.49)**	(22.78)**	(29.12)**	(17.12)**
log Indirect Costs					0.15	0.11	0.12	0.10
					(8.07)**	(4.51)**	(5.19)**	(3.47)**
HUMAN CAPITAL COEFFICIENTS								
Education	0.04	0.02	0.04	0.02	0.01	0.00	0.01	0.00
	(1.63)	(0.57)	(1.59)	(0.53)	(2.53)*	(0.35)	(2.11)*	(0.35)
Age	0.13	0.21	0.13	0.20	0.05	0.07	0.04	0.08
	(2.19)*	(3.08)**	(2.04)*	(3.09)**	(3.04)**	(2.59)**	(2.53)*	(3.01)**
Age^2 / 100	-0.20	-0.33	-0.19	-0.33	-0.07	-0.11	-0.06	-0.13
	(2.26)*	(3.46)**	(2.09)*	(3.49)**	(2.96)**	(2.82)**	(2.58)**	(3.33)**
Tenure	0.03	0.05	0.03	0.05	0.004	0.01	0.01	0.02
	(1.70)$^{+}$	(2.46)*	(1.43)	(2.56)*	(1.08)	(2.55)*	(1.35)	(3.47)**
DIAGNOSTICS & TESTS								
R^2	0.74	0.10	0.74	0.09	0.98	0.82	0.97	0.80
Quasi-concavity (proportion)	1.00	0.61			0.44	0.04		
Monotonicity (proportion)	1.00	0.00			0.69	0.04		
Homotheticity(2) (*p*-value)	0.30	0.64			0.25	0.68		
Homotheticity and CRS(3) (*p*-value)	0.36	0.21	0.39	0.04	0.31	0.49	0.86	0.06
Cobb-Douglas (*p*-value) (4)	0.49	0.82			0.00	0.00		

Table notes on the next page

Note: Time dummies are included in all regressions. The OLS regressions include controls for the age of the firm, industry, ownership structure and location. The numbers in ( ) are *t*-statistics based on standard errors robust to heteroskedasticity. Significance at the 1 per cent, 5 per cent and 10 per cent level is indicated by *, ** and $^{+}$ respectively.

(1) For the translog specification the marginal effects is a function of the inputs, and have therefore been evaluated at the sample means. For the Cobb-Douglas specification, the marginal effects are equal to the estimated coefficients.

(2) H_0: $\sum_k \beta_{km} = 0$, $m = 1,2,\ldots,J$ (see eq. [3]).

(3) For translog specifications, H_0: $\sum_k \beta_{km} = 0$, $m = 1,2,\ldots,J$, and $\sum_k \beta_k = 1$. For Cobb-Douglas specifications, H_0: $\sum_k \beta_k = 1$ (see eq. [3]).

(4) H_0: $\beta_{km} = 0$, $k = 1,2,\ldots,J$; $m = 1,2,\ldots,J$ (see eq. [3]).

TABLE 3
SYSTEM GMM ESTIMATES OF PRODUCTION FUNCTION PARAMETERS

	Dependent variable: log Value-Added[a]		Dependent variable: log Output[b]	
	[1] Translog	[2] Cobb-Douglas	[3] Translog	[4] Cobb-Douglas
MARGINAL EFFECTS[1]				
log Employment	0.88	0.73	0.10	0.17
	(4.20)**	(3.25)**	(0.93)	(2.37)*
log Capital	0.25	0.31	0.08	0.09
	(2.49)*	(3.58)**	(1.61)	(2.06)*
log Raw Materials			0.68	0.68
			(12.58)**	(14.02)**
log Indirect Costs			0.13	0.06
			(2.35)*	(1.14)
HUMAN CAPITAL COEFFICIENTS				
Education	-0.01	-0.003	0.01	0.006
	(0.82)	(0.07)	(0.65)	(0.35)
Age	0.24	0.26	0.04	0.07
	(2.40)*	(3.11)**	(1.42)	(2.61)**
Age^2 / 100	-0.38	-0.41	-0.08	-0.11
	(2.60)**	(3.35)**	(2.07)*	(2.88)**
Tenure	0.04	0.05	0.01	0.02
	(0.76)	(1.25)	(1.48)	(1.89)$^+$
DIAGNOSTICS & TESTS				
Quasi-concavity (proportion)	0.52		0.44	
Monotonicity (proportion)	0.87		0.59	
Homotheticity[2] (*p*-value)	0.63		0.46	
Constant returns to scale[2] (*p*-value)	0.74	0.85	0.59	0.92
Cobb-Douglas (*p*-value)[2]	0.66		0.37	
m1 (*p*-value)[3]	0.00	0.00	0.01	0.00
m2 (*p*-value)[4]	1.00	0.93	0.81	0.15
Sargan-Hansen (*p*-value)[5]	0.57	0.79	0.42	0.39

Note: Time dummies are included in all regressions. The numbers in ( ) are *t*-statistics. Significance at the 1 per cent, 5 per cent and 10 per cent level is indicated by *, ** and $^+$ respectively. Hypothesis tests are based on robust, finite sample corrected standard errors (see footnote 13) calculated using the method proposed by Windmeijer (2000).

a) The instrument set for the differenced equation consists of the levels of employment, physical and human capital, in periods t-2 and t-3. The instrument set for the levels equation consists of employment, physical and human capital, differenced, in period t-1, a constant and year dummies.

b) The instrument set for the differenced equation consists of the levels of employment, raw material, indirect costs and physical and human capital, in periods t-2 and t-3. The instrument set for the levels equation consists of employment, raw material, indirect costs and physical and human capital, differenced, in period t-1, a constant and year dummies.

Table notes continue on the next page

Table notes, continued

(1) For the translog specification the marginal effects is a function of the inputs, and have therefore been evaluated at the sample means. For the Cobb-Douglas specification, the marginal effects are equal to the estimated coefficients.

(2) See Table 2.

(3) Tests the null hypothesis that the differenced residuals in periods t and t-1 are uncorrelated.

(4) Tests the null hypothesis that the differenced residuals in periods t and t-2 are uncorrelated.

(5) Tests for the instrument validity.

TABLE 4
CORRELATES WITH THE FIXED EFFECTS IN THE PRODUCTION FUNCTION

	Fixed Effects from Column [4], Table 3	
	Coefficient	*t*-value
SECTORS[(a)]		
Food	0.108	1.89^{+}
Textiles or Garments	-0.126	1.83^{+}
Wood	0.242	2.43*
Furniture	-0.084	1.31
LOCATION[(b)]		
Accra (Capital City)	0.072	1.02
Kumasi	0.022	0.29
Cape Coast	-0.056	0.44
OTHER COMPANY CHARACTERISTICS		
Firm Age/100	0.055	0.29
Any Foreign Ownership	-0.011	0.21
Ghanaian State Ownership	0.032	0.34
R^2	0.16	
F-test slope coefficients		3.03**
Number of firms	143	

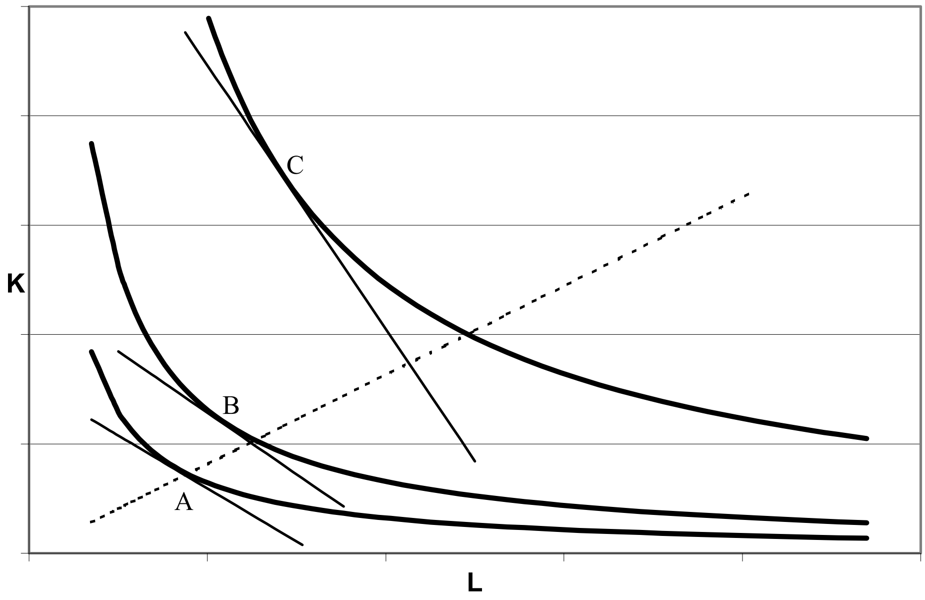
Note: The dependent variable is the estimated fixed effect from Column [4], Table 3. The estimation method is OLS. *t*-values are based on robust standard errors. Significance at the 10 per cent and 5 per cent level is indicated by $^{+}$ and *, respectively.

[(a)] Omitted category: Metal.

[(b)] Omitted category: Takoradi.

FIGURE 1
TECHNOLOGY AND FACTOR PRICES

A. Homothetic Technology, Variable Factor Price Ratio



B. Non-Homothetic Technology, Constant Factor Price Ratio

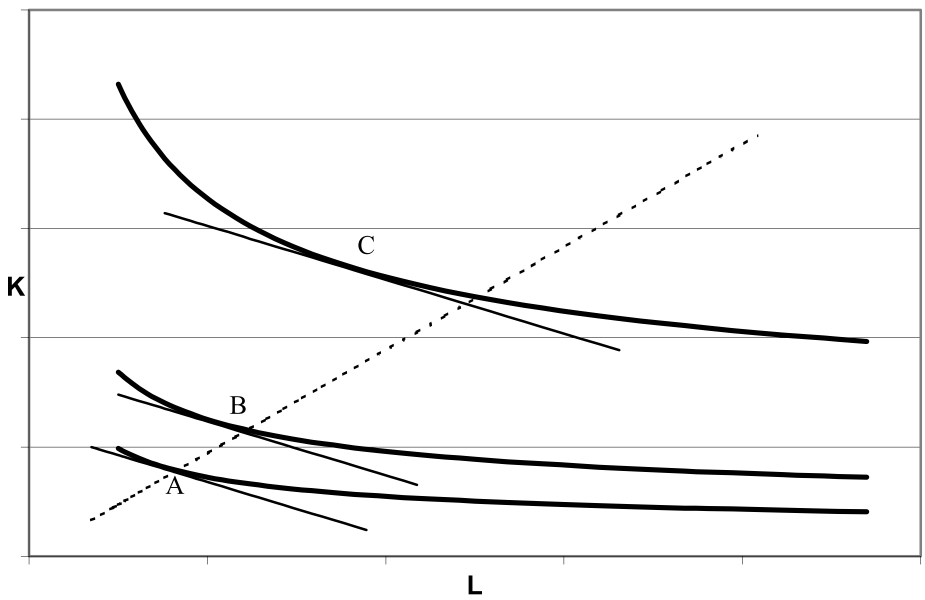
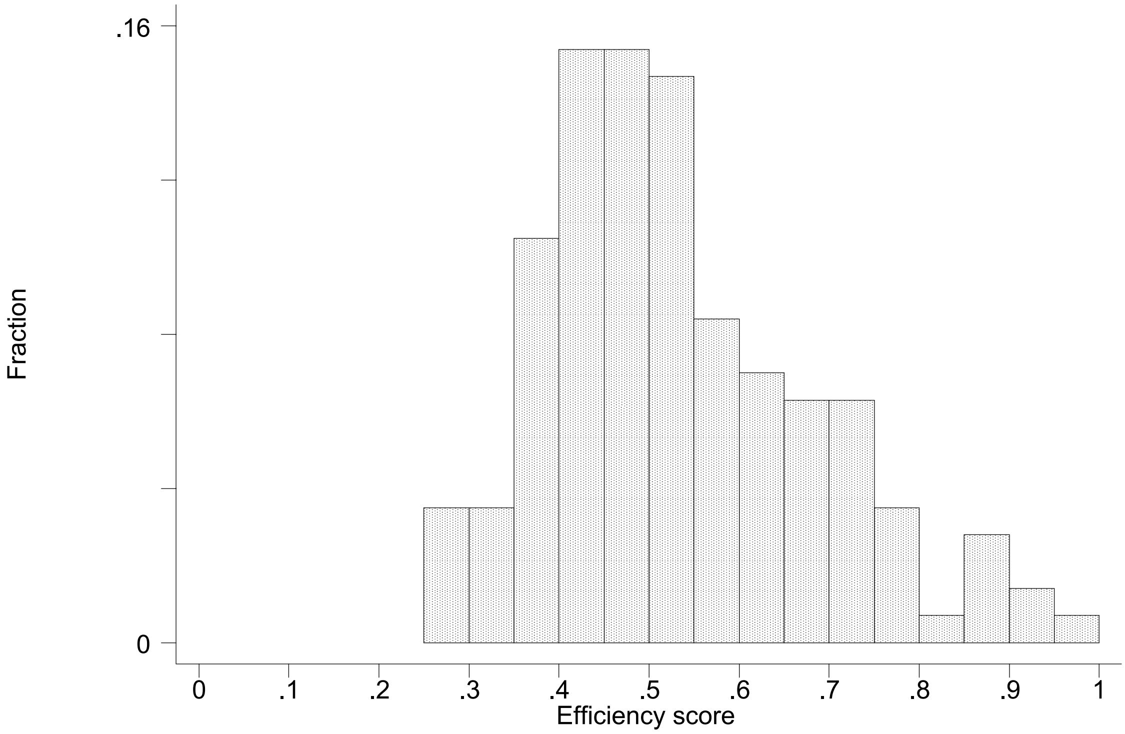
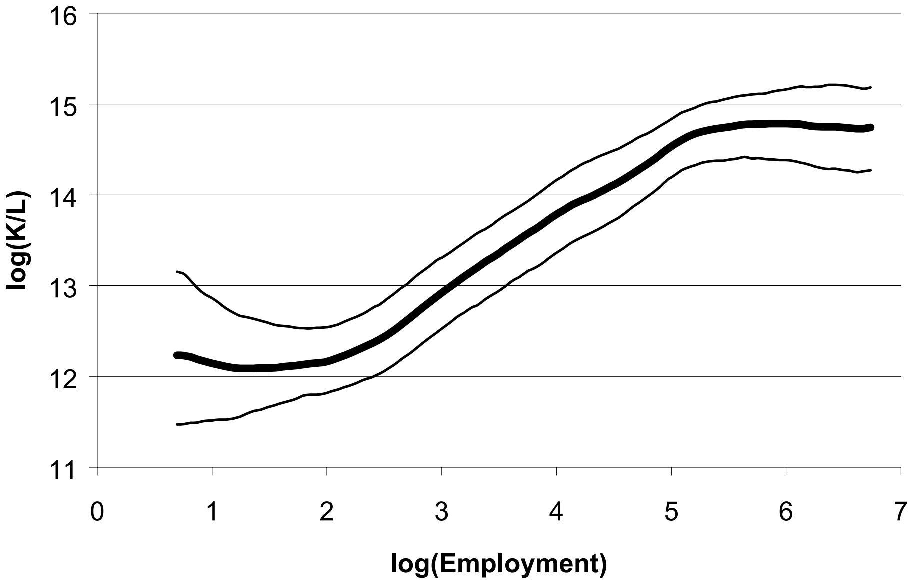


FIGURE 2
THE DISTRIBUTION OF TECHNICAL EFFICIENCY



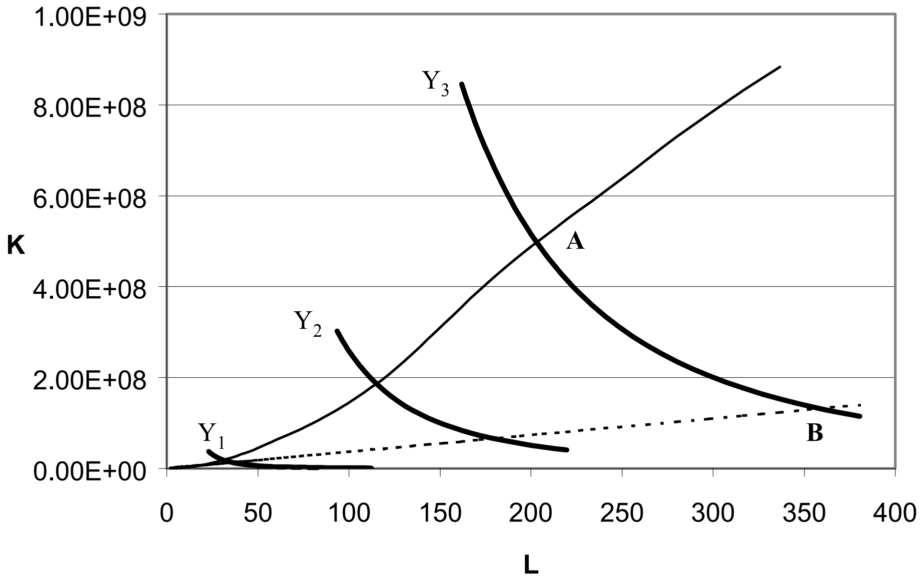
Note: Technical efficiency is defined as $te_i = e^{-(\hat{\mu}_{\max} - \hat{\mu}_i)}$, where $\hat{\mu}_{\max}$ is the sample maximum of the estimated fixed effects, and $\hat{\mu}_i$ is the estimated fixed effect for firm i. This is interpretable as a measure of the dispersion across firms of productivity, conditional on inputs and human capital. The estimated mean of technical efficiency is 0.53 and the estimated standard deviation is 0.15. The fixed effects estimates are based on the regression in Column [4], Table 3.

FIGURE 3
NON-PARAMETRIC REGRESSION: ln(*K*/*L*) = *f* (ln *L*) + error



Note:
The kernel is Epanechnikov and the bandwidth is equal to 1.27. The thin lines indicate pointwise 95% confidence intervals, calculated from 800 bootstrapped replications. To take the panel nature of the data into account we bootstrapped from the firms rather than from the observations, which is a similar procedure to that used by Deaton (1997, pp 216-218) for clustered data.

FIGURE 4
TECHNOLOGY, FACTOR PRICES AND FACTOR CHOICE IN GHANAIAN MANUFACTURING



A: K = 478 million Cedis; L = 207; K/L = 2.3 million Cedis.
B: K = 132 million Cedis; L = 358; K/L = 0.4 million Cedis.

Notes: The underlying production function is $\ln Y = \ln A + 0.3 \ln K + 0.7 \ln L$, where A is a constant. Y_1, Y_2 and Y_3 depict three isoquants under this technology, with $Y_2 = 5Y_1$ and $Y_3 = 10Y_1$. The solid line starting in the origin is the empirical expansion path, derived from the non-parametric regression shown in Figure 3. The dashed line starting in the origin is a hypothetical expansion path for relative factor prices constant at the level observed for a firm with 18 employees.

Appendix 1: The system GMM estimator

This appendix provides a brief description of the system GMM estimator. For more details see Blundell and Bond (1998).

Consider

(A1) $$y_{it} = x'_{it}\beta + \mu_i + \varepsilon_{it}\,, \qquad t = 1,2,\ldots,T,$$

where i and t are firm and time indices, y_{it} is the dependent variable, x_{it} is a row vector of order k of explanatory variables possibly including lags of the dependent variable, β is a column vector of parameters of order k, μ_i is a fixed effect potentially correlated with x_{it} and ε_{it} is a residual potentially correlated with x_{it}. To eliminate the fixed effect we take first differences:

(A2) $$\Delta y_{it} = \Delta x'_{it}\beta + \Delta\varepsilon_{it}\,, \qquad t = 2,3,\ldots,T.$$

If Δx_{it} is correlated with the differenced residual, the standard OLS estimator will be biased and inconsistent. However, assume that there exists a set of instruments that enable us to form a vector of moment conditions of order q, defined as

(A3) $$E\left(z'_{it}\Delta\varepsilon_{it}\right) = 0\,.$$

Provided $q \geq k$, we can obtain a consistent GMM estimator of β by minimising the quadratic

(A4) $$J\left(\hat{\beta}_{GMM}\right) = \bar{g}\left(\hat{\beta}_{GMM}\right)' W_N^{-1}\bar{g}\left(\hat{\beta}_{GMM}\right),$$

where $\bar{g}(\cdot)$ is the sum over the sample moment conditions of the form in (A3) and W_N^{-1} is a weight matrix (Hansen, 1982). A common procedure is to use lags of x_{it} as instruments for the differenced equation (A2), and because more instruments become available for higher t, we can form a matrix of instrument as

(A5) $$\mathbf{z_i} = \begin{bmatrix} x_{i1} & 0 & 0 & \ldots & 0 & \ldots & 0 \\ 0 & x_{i1} & x_{i2} & \ldots & 0 & \ldots & 0 \\ . & . & . & \ldots & . & \ldots & . \\ 0 & 0 & 0 & \ldots & x_{i1} & \ldots & x_{i,T-l} \end{bmatrix} \begin{array}{l} t = 1 + l \\ t = 2 + l \\ \\ t = T \end{array}$$

where l is the lag length in use. The resulting differenced GMM estimator often performs poorly in practice due to the problem of weak instruments. Blundell and Bond (1998) proposed combining the differenced equation (A2) with the levels equation (A1), for which lagged *differences* of the explanatory variables may serve as valid instruments. The vector of moment conditions is then defined as

(A6) $$E\left(\mathbf{z_i^+}'\mathbf{u}\right) = 0\,,$$

where

(A7) $$\mathbf{u}_i = \begin{bmatrix} \Delta\boldsymbol{\varepsilon}_\mathbf{i} \\ \boldsymbol{\varepsilon}_\mathbf{i} \end{bmatrix}$$

and

(A8) $$\mathbf{z_i^+} = \begin{bmatrix} \mathbf{z_i} & 0 & 0 & \ldots & 0 \\ 0 & \Delta x_{i1} & 0 & \ldots & 0 \\ 0 & 0 & \Delta x_{i2} & \ldots & 0 \\ . & . & . & \ldots & . \\ 0 & 0 & 0 & \ldots & \Delta x_{i,T-l} \end{bmatrix} \begin{array}{l} \\ t = 1 + l \\ \\ \\ t = T \end{array}$$

The system GMM estimates are then obtained by minimising (A4).