PRODUCTION TECHNOLOGY AND TECHNOLOGICAL PROGRESS

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Abstract:

In this paper we investigate production technology in the manufacturing sector using firm-level panel data from Africa and macro panel data covering a large number of developing and developed economies. Our work makes three major contributions to the literature attempting to explain cross-country income differences. Firstly, we redefine the technology frontier to include input coefficients along with the standard Total Factor Productivity. Our empirics reveals significant and important parameter heterogeneity across countries. Secondly, we include intermediate inputs and use gross output as our measure of production as well as estimating, rather than assuming and backing out, the frontier. Finally, we consider the hitherto unexplored link between micro and macro data. Despite the firm being the ultimate unit of production, and hence the determinant of income, the extensive firm datasets now available have been neither used to understand cross-country income differences nor as a direct complement to the macro data.

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1. INTRODUCTION

Accounting for the huge income differences observed between countries has rightly been an enduring topic of research for the economics profession. At the macro level, the growth accounting approach has been dominant and takes as its starting point a value-added aggregate production function of the form:

$$Y_{it} = A_{it} K_{it}^{\beta} L_{it}^{1-\beta} \tag{1}$$

where K represents the capital stock, L is the labour force, Y is value-added, A is Total Factor Productivity (TFP) and the coefficient β is assumed to be close or equal to one third. Differences in output per worker can then be attributed to either differences in the amount of capital per worker or differences in TFP. This growth accounting approach does not require any estimation, and such studies find that unexplained TFP is the major determinant of income differentials across countries (Hall & Jones, 1999; Caselli, 2005; Hsieh & Klenow, 2010). Many authors have noted that this is an unsatisfactory explanation as it is only identifying the proximate cause. If TFP *does* account for the large income differences across countries, then what we need to be concerned about is what underlying processes are being captured by TFP.

A common approach to try to increase the explanatory power of inputs and to explain what may be behind TFP is to relax some of the assumptions implicit in Equation (1). For example, the measure of L can be augmented with measures of education (Hall & Jones, 1999) or the proportions of skilled and unskilled workers (Caselli & Coleman II, 2001), the Cobb-Douglas functional form can be generalised (Jerzmanowski, 2007), or value-added can be corrected for rents accruing to natural capital (Caselli & Coleman II, 2006). While the proportion of variation in output per worker put down to TFP is generally reduced with each generalisation, it still remains significant (Hsieh & Klenow, 2010). Caselli (2005) surveys this literature and concludes that none of these generalisations can satisfactorily explain the wide TFP differentials.

In a comprehensive meta-study, Jorgensen (1990) finds that input growth accounted for most of the output growth in the United States over the period 1947-1985, and notes that this finding is not confined to that particular country or time period. This is in stark contrast with the cross-country literature, which typically finds that inputs are much less important than TFP. This is suggestive that the TFP puzzle in the cross-country literature is related to the modelling of inputs. We investigate a further three possibilities:

(i) the difference is an artefact of the value-added specification and the bias caused by ignoring material inputs which may be more important in poorer countries.
(ii) the technological frontier, as given by the coefficients on inputs *as well as* TFP, differs across countries.
(iii) the aggregation in the macro data may be masking true patterns revealed at the micro level.

Two assumptions implicit in Equation (1) are that the production function is value-added and all countries have a common technology. We have cause to doubt the former assumption not only because it relies upon some very specific technical conditions, but because it will give a biased estimate of productivity and because we believe that raw materials may be used in different ways across economies. The latter assumption of common technology is challenged by the 'appropriate technology' literature, which argues that different technologies are appropriate to different factor endowments. Under this explanation, the R&D leaders develop productivity-enhancing technologies that are suitable for their own capital-labour ratios and cannot be used effectively by poorer countries and so the latter do not develop. Empirical evidence which lends some support to this hypothesis can be found, among others, in Clark (2007) and Jerzmanowski (2007). We generalise the manner in which technologies can be made appropriate while also incorporating multiple inputs.

There exists now a large number of firm-level datasets available for a wide range of countries, and these have been used to investigate issues of productivity in individual countries (Lall, Tan, & Tan, 2002; Söderbom & Teal, 2004) and, in a more limited way, in groups of similar countries (Clerides, Lach, & Tybout, 1998; Hallward-Driemeier, Iarossi, & Sokoloff, 2002; Rankin, 2004). This opens up the possibility of making more comprehensive use of this data, in an analogous way to the usual macro approach, to investigate cross-country productivity differentials *at the micro level.* Some of the factors that are important for productivity at the micro level also show up as important in the macro data, however, others do not. This could imply that the aggregation into macro data is hiding some important processes, or that there are different forces at work at the macro and micro levels.

In a gross output framework, we test empirically for the existence of different technologies, as well as for different levels of TFP, across countries. A finding of technological heterogeneity is a necessary condition for the appropriate technology hypothesis to hold. Such heterogeneity then leads to the question of whether poor countries are using a different technology through choice or through constraint.[1] For example, it is well known that poor countries have lower capital-labour ratios. Is this because investment is constrained by lack of finance, or is it a rational response to a riskier environment? Constraints would point to policy recommendations aimed at bringing factor ratios more in line with those of R&D leaders; whereas, choice would suggest policies focused on efficiency, 'appropriate innovation' and changes in the business environment. In the event of no heterogeneity detected across countries, then poor countries should adopt the existing technologies and efficient techniques of richer economies.

Section 2 gives the theoretical background, particularly in relation to intermediate inputs and parameter heterogeneity. Sections 4 and 3 contain the empirical analysis at the macro and micro levels respectively, while Section 5 brings the two sets of results together. Finally, Section 6 presents the conclusions of this exercise.

2. REDEFINING THE TECHNOLOGY FRONTIER

We redefine the world technology frontier as[2]

$$\ln Y_{it} = \alpha_{it} + \beta_{i,K}\ln K_{it} + \beta_{i,L}\ln L_{it} + \beta_{i,M}\ln M_{it} + \phi_i(E_{it}) \tag{2}$$

The log-linearised empirical production function in Equation (2) differs from Equation (1) in that it (i) allows the coefficients β and the function ϕ to differ across countries, (ii) explicitly includes human capital E, (iii) includes material inputs M, and uses gross output rather than value-added as the output measure Y. The idea that the world technology frontier is a locus encompassing many individual frontiers is in line with the model of Jones (2005).

Before proceeding further, it is important to define what we mean by technology. In an intuitive sense technology describes the way in which inputs are transformed into outputs. Despite many authors having posited the idea that technology differs across countries, in previous empirical studies this cross-country heterogeneity has only been allowed to exhibit itself through variations in the TFP term (Hall & Jones, 1999; Jones, 2005).[3] Caselli and Coleman II (2006) also admit the possibility

[1]Examples of possible constraints are a lack of skilled labour, a lack of good technologies for low capital-labour rations, lack of managerial skill, or a lack of finance to allow expansion of the capital stock.

[2]In the micro data, greater disaggregation of inputs allows us to further separate material inputs into two subcategories.

[3]Although some authors, including Harrigan (1999) allow for the βs to differ by sector, but not country.

of heterogeneity by employing a 2-input CES production function where the *efficiency* with which capital and labour are used is allowed to differ (this is a technology difference under their terminology). We want to allow for the *way* in which inputs are used to differ across countries, as well as the *efficiency* with which they are used. While not wanting to get too hung up on definitions, we argue that the former is captured in β and ϕ, while the latter is captured in α.[4] Thus we take a more generalised view of technology by allowing the coefficients β and the function ϕ, as well as α, to differ across countries. Note that, for the remainder of the paper, when we refer to the technological coefficients β this is to be taken to include the function ϕ.

The study closest in approach to ours is Jorgensen, Kuroda, and Nishimizu (1987). They compare sectoral productivity across the US and Japan and allow for the input coefficients to vary across countries, and also use a gross output production function. However, our methodological approach differs from theirs in that they calculate an index of productivity rather than estimating productivity or the other parameters of the production function.

Cross-country empirical analysis of growth, productivity and development has for some time now been recognised as deeply flawed, plagued by endogeneity concerns and lack of robustness of results across samples and specifications, where the latter is commonly meant to imply covariates entered in the regression equation ('growth determinants'), rather than concerns over static versus dynamic, homogeneous versus heterogeneous specification among others. Charting the development of this literature from the seminal papers by Mankiw, Romer, and Weil (1992) and Islam (1995) to somewhat neglected recent attempts, Eberhardt and Teal (2011) highlight two issues: firstly, that the vast majority of empirical studies of cross-country relationships adopt an empirical framework akin to the Mankiw et al. (1992) convergence equation (this applies in particular to the model-averaging literature) or the dynamic panel model of Islam (1995); and secondly, that the evolution of cross-country empirics represents a gradual relaxation of multiple assumptions related to technology heterogeneity (in the sense of our use of the terminology), variable time-series properties and cross-country correlation, although as the previous point suggests these concerns are not adopted in the vast majority of studies. A conclusion to be drawn from this discussion is that over the past decade econometric theory, in form of the panel time series literature, has provided a readily-available toolkit to investigate cross-country macro panels allowing for much less stringent assumptions on specification and data properties. Most recent work by Pedroni (2007), Cavalcanti, Mohaddes, and Raissi (2009), Costantini and Destefanis (2009) and Eberhardt and Teal (2010) points the way in addressing the three main concerns in this literature, namely nonstationarity, technology heterogeneity and cross-section correlation.

2.1 Intermediate Inputs

An important feature of this paper is its use of a gross output production function. Gross output is the physical quantity of goods that are produced by firms, sectors and economies and thus the gross output production function contains the ultimate source of productivity and technology. Value-added production functions can be useful in analysing the flow of income to factors, however, whether or not one takes the view that value-added measures are of interest, the correct approach is to estimate a gross output production function. Value-added measures can then be easily derived. Given the strenuous requirements for the value-added production function to be valid (Jorgensen, 1990), the gross output production function is to be preferred when analysing productivity, particularly at the firm level. This is especially so seeing as though the unit of production is gross output: firms do not manufacture value-added. Harrigan (1999) concurs with this view and writes that the gross output

[4]The definition need not be so clear cut, and it is possible that α itself may be a function of inputs, as has been suggested by Jerzmanowski (2007).

production function "is undoubtedly the most theoretically appealing and least restrictive method of making productivity comparisons", while Jorgensen (1990) states that "incorporation of intermediate inputs is an important innovation." Despite this, there is scant empirical evidence on the role of intermediates and how this varies across countries.

There are a number of papers which include some form of intermediate inputs in cost functions at the sector or country level. Most of these studies are part of the literature which sought to ascertain whether capital and energy were complements or substitutes (Thompson & Taylor, 1995). A large number of these studies are summarised in Frondel and Schmidt (2006), who additionally provide evidence that macro level cost functions produce biased results if materials are not included. Our cross-country sectoral level dataset allows us to include materials and pursue a production function approach at the macro level.

Of the few cross-country comparisons at the micro level, only a small subset consider the role of intermediate inputs. Two previous studies which do so are Eifert, Gelb, and Ramachandran (2005) and Baptist and Teal (2008). The latter paper will be the focus of the analysis in Section 3. The former focuses on the role of indirect costs in production, and also presents both macro and micro evidence. They argue that high indirect costs are reflective of the poor investment climate in Africa and that ignoring intermediate inputs is too narrow a view of firm performance in Africa. We take this a step further and include indirect inputs as part of the production function.

Biases from value-added production functions can come from a failure to meet the technical separability conditions, imperfect competition (Basu & Fernald, 1995), changes in the rate of outsourcing, or from heterogenous technology. Here we focus on the latter bias. When the production process uses multiple inputs a decision has to be taken on a weighting to come up with an overall measure of 'inputs'. Representing this weighting function in the gross output and value-added contexts as F and V respectively, and considering three inputs for simplicity, we can write productivity as:

$$A_{GO} = \frac{Y}{F(K, L, M)} \qquad \text{or} \qquad A_{VA} = \frac{Y - M}{V(K, L)} \tag{3}$$

The functions V and F can have a number of forms, such as the Cobb-Douglas $F = K^{\beta_K} L^{\beta_L} M^{\beta_M}$. A productivity improvement that allows an output of $Y + \Delta Y$ to be produced from the same inputs can be quantified as follows:

$$\Delta A_{GO} = \left(\tfrac{Y+\Delta Y}{F(K,L,M)}\right) \div \left(\tfrac{Y}{F(K,L,M)}\right) = 1 + \frac{\Delta Y}{Y} \tag{4}$$

$$\Delta A_{VA} = \left(\tfrac{Y+\Delta Y-M}{V(K,L)}\right) \div \left(\tfrac{Y-M}{V(K,L)}\right) = 1 + \frac{\Delta Y}{Y-M} \tag{5}$$

It is possible to unambiguously sign the direction of the bias in measured productivity growth from using value-added data. Using value-added measures will overstate productivity growth, and the size of the bias will be increasing in materials. This is intuitive: the same multifactor productivity improvement is being attributed to a subset of the inputs. If we interpret the functions F and V as production functions, then, the bias is invariant to the function so long as the productivity term is multiplicative. Comparison becomes clouded if we allow the productivity change to also involve a change in technology. However, if we assume that the gross output changes in such a way so as to make the share of materials fall by ΔM while keeping the value of $F(K, L, M)$ constant (through substitution), then the bias on the value-added measure increases by $\frac{\Delta M}{Y-M}$.

In an econometric context, consider what the bias will be if the true model is given by Equation 2 but we estimate Equation (6) — assume for simplicity that labour is quality-adjusted. The value-added specification is given by:

$$\begin{aligned} \ln V &= \ln a + b_K \ln K + b_L \ln L, & (6)\\ V &= Y - M & (7)\end{aligned}$$

Letting p_R represent the price of factor R, the first order conditions for profit maximisation imply that:

$$M = \left[\frac{Y}{A} \left(\frac{p_K}{\beta_K}\right)^{\beta_K} \left(\frac{p_L}{\beta_L}\right)^{\beta_L} \left(\frac{\beta_M}{p_M}\right)^{\beta_K+\beta_L} \right]^{\frac{1}{\beta_K+\beta_L+\beta_M}} \tag{8}$$

which, assuming constant returns to scale for simplicity and because that restriction is not rejected by our data, we write as $M = \gamma \frac{Y}{A}$. In order to understand the bias in the coefficients in Equation 6 we want to express the true model in a form that corresponds to the incorrect model and then compare coefficients. Repeated substitution of Equation (2) into Equation (6), using (equations 7) and (8), gives

$$\begin{aligned} \ln V &= \ln Y + \ln\left(1 - \frac{M}{Y}\right) & (9)\\ &= \ln Y + \ln\left(1 - \frac{\gamma}{A}\right) & (10)\\ &= \ln A + \beta_K \ln K + \beta_L \ln L + \beta_M \ln M + \ln\left(1 - \frac{\gamma}{A}\right) & (11)\\ &= \ln A + \beta_K \ln K + \beta_L \ln L + \beta_M [\ln Y - \ln A + \ln\gamma] + \ln\left(1 - \frac{\gamma}{A}\right) & (12)\\ &\vdots \\ &= \ln A + \left(\frac{\beta_M}{1-\beta_M}\right)\ln\gamma + \ln\left(1 - \frac{\gamma}{A}\right) + \left(\frac{\beta_K}{1-\beta_M}\right)\ln K + \left(\frac{\beta_L}{1-\beta_M}\right)\ln L & (13)\end{aligned}$$

In a three-factor model with constant returns to scale, the bias in the value-added coefficents will therefore be as follows:

$$\ln a = \ln A + \left(\frac{\beta_M}{1-\beta_M}\right)\ln\gamma + \ln\left(1 - \frac{\gamma}{A}\right), \quad b_K = \left(\frac{\beta_K}{\beta_K+\beta_L}\right), \quad b_L = \left(\frac{\beta_L}{\beta_K+\beta_L}\right) \tag{14}$$

Given the biases from a value-added production function, and a suspicion that the way in which inputs are modelled is important, we adopt the gross-output specification in this paper.

2.2 Technological Heterogeneity

Many authors talk of technology differing by country, but almost universally define the technology frontier in terms of TFP, or A in Equation (1), and impose common βs across countries (Hall & Jones, 1999; Jerzmanowski, 2007). We have sufficient data at both the micro and macro levels to get estimates for these parameters and to allow these estimates to differ by country. Thus we define our technology frontier by the coefficients β, and allow a technology to be implemented with an independent level of TFP.

Caselli (2005) summarises the puzzle in the cross-country productivity literature as one of inputs having insufficient explanatory power. Intuitively, if we restrict all countries to the same technology then inputs will have less explanatory power than if we allowed them to choose an 'appropriate' technology from a menu of available technologies. Most appropriate technology models assume that technologies are generated for specific capital-labour ($K : L$) ratios, and are represented quantitatively by defining a function linking $K : L$ to A (Basu & Weil, 1998). It can be seen from Equation (8) that optimal factor ratios will be a function of prices and the technological coefficients β. How, then, does our characterisation of technology relate to that used in the appropriate technology literature? In a CRS Cobb-Douglas production function, first-order conditions give:

$$\frac{K}{L} = \frac{p_L}{p_K}\frac{\beta_K}{\beta_L}, \tag{15}$$

and analogously for other input pairs. So we can see that, in the 2-factor case with fixed prices, defining technology by the $K : L$ ratio is equivalent to defining it by the coefficients β. However, if one wishes to allow prices to change or allow for more than two factors, the usual appropriate technology definition becomes problematic. Factor prices may change due to any number of factors unrelated to technology and we wish to allow such changes without requiring firms to change technologies. In a multi-factor world with more variable inputs, it makes more sense to view the parameters β as fixed rather than fixing all pairs of factor ratios. Also, even if one were to believe that K:L was fixed at the national level, this is not true at the firm or sectoral level. A firm may choose to vary its factor ratios because it is using a new technology, or because of changes in relative factor prices, thus we prefer to view factor ratios of production units as functions of technology (and other parameters) rather than the other way around. In common with much of the cross-country growth literature, appropriate technology models also link technology to the TFP term. For the unique technology attached to a given K:L ratio, there is a fixed TFP term. Defining technology using the βs allows us to decouple TFP from technology and allow the same technology to be implemented with different levels of TFP across countries.

Incorporating technological heterogeneity is important if we are to accurately compare cross-country productivity. Equation (4) demonstrates how a value-added production function will bias measures of TFP. This argument has an obvious extension to the use of output per worker as a proxy for productivity where prices or technology differ across countries. Imagine two countries of the same size using a common 3-factor production technology with the same TFP level, but where relative wages are lower in one country than in the other. Then each country will choose different factor combinations while producing the same level of output. Clearly output per worker will be different in the two countries, even though they have the same TFP, and so the latter will not be an accurate measure of productivity (although may be useful in accurately reflecting relative incomes). This same argument applies if countries are using different production technologies. Different coefficients β will result in different factor ratios being chosen and so the use of output per worker as a measure of productivity is conflating true productivity differences with cross-country variations in prices and technology. Even when the correct measure of TFP is used, its value will be biased if coefficients are incorrectly assumed common.

Equation (14) tells us that the b-coefficients in the value-added model are purely determined by the relativity of the coefficients β_K and β_L in the gross output production function. Moreover, using the results from our preferred gross output specification in Table I, the implied $b_K \approx \frac{1}{3}$ for both Ghana and South Korea[5]. This is consistent with our empirical estimates of the slope coefficients of the value-added production function in each country (not reported) and also with the coefficients imposed by Hall and Jones (1999). Thus true technological heterogeneity in the gross output production function can be masked through the spurious use of a value-added specification to model the productive process. The estimate of the productivity term will also be biased, with the direction and

[5]Note that if we have CRS and a constant $\beta_K : \beta_L$ ratio, then technology would be uniquely indexed by a single parameter β_K. More specifically, in the context of Equation 2 with quality adjusted labour we have $ln\frac{Y}{M} = lnA + \beta_K[ln\frac{K}{M} + \rho ln\frac{L}{M}]$ where $\rho = \frac{\beta_L}{\beta_K}$.

size of the bias being a function of prices and technology.

Ethier (1982) provides a theoretical justification for being concerned about technological heterogeneity, especially in relation to intermediate inputs. Motivated by the inconsistency between Heckscher-Ohlin trade theory and the observation that post-WWII trade was dominated by the exchange of manufactures between similar developed economies, he incorporated intermediate goods into a model of international trade. His model suggests that firms value diversity in intermediate input availability, the relative share of final and intermediate goods will differ with the capital stock, and that intra-industry trade in intermediate components will be complementary to international factor movements. So we would expect that firms in different countries will use intermediate inputs in a different way. For example, firms operating in South Korea may be more likely to purchase sophisticated intermediate components, while firms in Ghana may be more likely to purchase raw materials and manufacture intermediates in-house. If this was the case, we would expect the material elasticity of final output to be higher in Ghana as they are purchasing unprocessed intermediates and transforming them in-house before using them to produce final output.

Eifert et al. (2005) also indirectly allow for the idea of technological heterogeneity. They equate indirect costs with the business climate and argue that firms facing different levels of indirect costs may use different technologies and business services. Their results support the idea that the share of indirect inputs is crucially linked to technological change. Their approach is, however, to estimate a value-added production function, which will be biased as per Section 2.1, and they also do not present their estimates of what we call the technological parameters. However they do show that indirect costs are large as compared to value-added TFP and highlight the error of simply considering value-added TFP alone. Our approach differs in that we model material inputs as an integral component of production technology.

There is also evidence to support the allowance for technological heterogeneity at the macro level. In the capital-energy substitution literature referred to in Section 2.1 cross-country heterogeneity is found where cost function coefficients are permitted to vary. Due to differences in specification we are not able to transform these results into a form which is directly comparable with ours. Caselli and Coleman II (2006) show that using a CES production function can increase the proportion of output differences which can be attributed to inputs substantially. Caselli (2005) undertakes sensitivity checks on Equation (1) by allowing α to vary and finds that the proportion explained is very sensitive to this choice, and also notes that there is very little empirical evidence as to whether and how this parameter differs between countries. These results suggest that the way in which inputs are treated is important, and hence we prefer to estimate rather than impose the input coefficients and also to allow them to vary by country.

2.3 Common properties of Macro Panel Data

In addition to the concerns regarding inputs specified in the empirical model and the concessions to parameter heterogeneity, macro panel data poses at least two further challenges to the econometrician, namely the integrated nature of its variables and processes and the potential for correlation across panel members. In the following we briefly introduce these issues; for a more detailed discussion of nonstationarity and cross-section dependence in cross-country production function estimation refer to Eberhardt and Teal (2011).

The notion of variable nonstationarity and its implications for estimation and inference are well-established in the time-series econometric literature and since the 1990s substantial progress has been made on the panel front (Levin & Lin, 1992; Im, Pesaran, & Shin, 1997; Bai & Ng, 2002; Pesaran, 2007). Once variables or unobserved processes are nonstationary, the potential for a spurious regression result arises and standard tools of inference such as t-statistics or F-tests are no longer reliable (Kao, 1999). A process or variable is nonstationary if over the long time-horizon it fails to return to constant mean or trend and in the analysis of macro production functions this characteristic seems intuitively plausible for stock variables such as capital and labour.

Over the recent decade panel econometricians have concerned themselves more intensively with a separate issue concerning the correlation of variables across panel units: just like correlation over time (autocorrelation) affects inference we can think of cross-section correlation as having a similar effect. Perhaps more seriously than these concerns over efficiency are suggestions that the coefficients of interest (in our case the technology parameters on the observable factor inputs labour, capital stock and materials) may be unidentified (Kapetanios, Pesaran, & Yamagata, 2011). The adopted framework to deal with cross-section dependence is that of an unobserved common factor model, which allows for the modelling of the equilibrium relationship studied (here the production function) as well as of the factor inputs as functions of unobserved latent variables ('factors'). These factors can be thought of as capturing global effects such the recent financial crisis or the economic impact of China's rise to economic might over the past decade, as well as more localised effects such as productivity spillovers from one country to its neighbour (and vice versa). Crucially, while the same latent factors may be driving output and inputs in all countries, the relative magnitude of their impact may differ: just like the impact of observable inputs on output may differ across countries and/or sectors (technology heterogeneity), that of unobserved processes, which in the production function context can be thought of as TFP, may differ as well.

A number of empirical estimators (Bai & Kao, 2006; Pesaran, 2006; Bai, Kao, & Ng, 2009) are available to deal with all the concerns about heterogeneity, nonstationarity and cross-section correlation. Of these the Pesaran (2006) common correlated effects (CCE) estimators have the advantage of being easy to implement as well as less reliant on a large time-series dimension than the alternative methods, and we therefore employ these in the empirical analysis of macro data.

Using the theoretical framework outlined above, that is, allowing for intermediate inputs and technological heterogeneity (as well as variable nonstationarity in the macro data), we now move to consider the empirical evidence at both the micro and macro level.

3. MICRO EMPIRICS

In this Section we present the empirical evidence for technological heterogeneity and cross-country productivity differentials at the micro level. This Section is based upon results contained in Baptist and Teal [2008a,b] and those papers contain more detail on the datasets and the estimation techniques which are not presented in full detail here for brevity. The relevant empirical findings are presented in Tables I and II.

Our panel data come from firm-level surveys of manufacturing firms across six countries at various stages of development, predominantly in Sub-Saharan Africa: Ghana, Kenya, Nigeria, South Africa, South Korea and Tanzania. The length of the panel ranges from a minimum of two years in South Africa to a maximum of 12 years in Ghana, and the number of firms in each country ranges from a minimum of 147 in South Africa to a maximum of 357 in South Korea. The Sub-Saharan African data were collected as part of the Regional Program on Enterprise Development (RPED) , while the South Korean data were collected by the World Bank [2001] and are described in Hallward-Driemeier (2001).

While physical inputs incorporate many of the major factors determining the output of the firm, there are some firm-specific variables which remain unobserved, such as management skill. If these unobserved characteristics are correlated with input levels then endogeneity may be a concern for ordinary least squares regression models — see Eberhardt and Helmers (2010) for a detailed discussion of 'transmission bias and the various solutions suggested in the literature. Fixed effects and System GMM estimators are explored as possible mechanisms to remove any bias. Fixed effects estimation will remove any bias caused by firm-specific time-invariant unobservables, such as management skill or initial conditions, while the inclusion of year dummies will account for time-specific unobservables common to all firms. The fixed effects estimator will still be subject to endogeneity bias from correlation between current period idiosyncratic firm-specific factors and current input levels. As we have panel data with a reasonable time dimension, the System GMM estimator by Blundell and Bond (1998) is used in an attempt to control for this latter type of endogeneity bias. This estimator exploits the autocorrelation structure of the residuals to provide instruments. Consider, for example, that current-period productivity shocks may be correlated with current input levels, but not with past input levels. Sufficiently lagged differences may then be used as instruments for contemporaneous levels while lagged levels are instruments for the equation in first differences. All standard errors are calculated in a way which is robust to heteroskedasticity and autocorrelation. In addition, the standard errors for the OLS and FE regressions have been calculated using a clustering method that allows for the errors to be correlated within firms observed in multiple time periods but independent between firms.

[Table I about here]

Baptist and Teal (2008) show that output per worker differentials between Ghanaian and South Korean firms result from a difference in production technology and a difference in the firm-level returns to worker education. Once these two elements were taken into account it was not possible to identify a significant difference in TFP in firms across the two countries. More specifically, Ghanaian manufacturing firms use a technology that is more intensive in its use of raw materials, and less intensive in its use of capital and skilled labour, than that used by South Korean firms. The number of years of schooling received by workers in manufacturing firms in the two countries is similar, but the returns to education experienced by the firm are very weak and convex in Ghana and strong and concave in South Korea. The average returns are 10.8% in South Korea and 2.6% in Ghana. As well as running a gross output specification as in Equation 2, they run a value added regression along the lines of Equation 1 and find that the value added coefficients are similar but TFP is substantially higher in South Korea. That is, a value-added production function does not accurately reflect the differences, or lack thereof, in technology and TFP across the two countries.

[Table II about here]

A similar pattern is observed within Africa. Table II presents Cobb-Douglas production functions for the 5 African countries in our dataset. Tests of technological difference are conducted by interacting country dummies with the input coefficients, and these establish a pattern of three different technologies consistent with the Ghana-South Korea difference. It is not possible to reject the null that the interactions between Ghana, Kenya and Nigeria are jointly insignificant, while a null of no difference between this group and each of Tanzania and South Africa is rejected. Returns to scale do not differ across technologies but there is variation in the output elasticities. Interacting dummies for foreign ownership, export status and sector proved insignificant. Firms in a country are not just distinct from those in other countries on average, but also if the sample is restricted to a single sector. Technology choice under local conditions rather than constraint is further supported by the fact that foreign-owned firms are not using different technologies. Human capital was not available for South

Africa or Nigeria however, for those countries for which it was available, Baptist and Teal (2008) confirm the result that technological heterogeneity and differences in the return to education can fully account for TFP differences. The rate of return on education in Tanzania and Kenya is similar to that of Ghana: low and weakly convex.

The result that, at the micro level, TFP differences can be completely explained by differences in the returns to education and the way in which inputs are used (ie technology) is surprising. Of course, it does not mean at the proximate level that South Korean firms are not more productive, but we are able to be more specific about *where this difference is coming from* rather than leaving it as unexplained TFP. There is some evidence from other studies which supports our finding. Clark (2007) presents historical evidence, including from individual plants, that the efficiency with which labour is used is the key differential between firms in rich and poor economies. Even in cases where identical capital equipment and managers were available, firms in poorer countries used different factor combinations to those in richer countries, and the major difference was in labour inputs. Jerzmanowski (2007) presents evidence which suggests that skilled labour cannot be productively used without sufficient capital, but that sophisticated capital can be successfully employed without skilled workers. This is consistent with our finding that the returns on skills are much lower in poorer economies. The extensive policy focus on improving human capital in developing countries has not led to major gains in incomes due to lack of investment in capital or inappropriate production techniques.

[Figure I about here]

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

4. MACRO EMPIRICS

In this Section we present the empirical evidence for technological heterogeneity and cross-country productivity differentials at the macro level. We first review the relevant empirical literature and introduce the dataset. Various pre-estimation tests are carried out, with results reported in the appendix.

In empirical studies of growth and development (typically using the 'Penn World Tables' (PWT) of aggregate economy data (Heston, Summers, & Aten, 2009)) researchers often investigate 'productivity' (also 'total factor productivity' or TFP) levels and growth rates and contrast them with factor inputs in their explanatory power for income variation across countries and time (Mankiw et al., 1992; Young, 1995; Hall & Jones, 1996; Klenow & Rodriguez-Clare, 1997; Easterly & Levine, 2002). However, since the seminal contributions of Barro (1991) and Mankiw et al. (1992) introduced the standard framework of growth empirics (Temple, 2006), the *compositional* heterogeneity between industrial powerhouses such as the United States and many Sub-Saharan African countries whose economies are (still) to a large extent dominated by subsistence agriculture has been glossed over: the PWT provide the aggregate data, and thus to many researchers an aggregate cross-country growth regression seems the only meaningful way to analyse growth and development. Few empirical studies investigate detailed industrial sub-sectors in a large N dataset — with the exception of some studies analysing broad sectors (agriculture, mining, manufacturing) in OECD countries (Bernard & Jones, 1996b, 1996a; Harrigan, 1999; Malley, Muscatelli, & Woitek, 2003) or 'manufacturing versus agriculture productivity' in a diverse sample of countries (Martin & Mitra, 2002; Eberhardt & Teal, 2011), one of the few studies we found including both developed and developing countries is by Yeaple and Golub (2007). Their investigation of a set of ten manufacturing sectors focuses on the impact of infrastructure variables on growth. Thus there are few if any empirical papers analysing *all* sectors of production, or all subsectors of an industrial division, such as manufacturing in one study.

`[Table III about here]`

We analyse data for manufacturing subsectors (28 sectors, following the ISIC3 classification) taken from Nicita and Olarreaga (2007) — for more details see the Data Appendix. Manufacturing and its development is commonly seen as one of the key factors for development, with the 'East Asian Miracle' economies a frequently cited showcase (Page, 1994). For a large sample including low-, middle- and high-income countries, it would seem a very strong assumption that the productive process were adequately represented by a homogeneous Cobb-Douglas production function: this neglects the differential distribution of labour and output across diverse sectors such as Apparel (labour-intensive, predominantly low-cost), Chemicals (capital-intensive) or Machinery (somewhere inbetween) production.

`[Table IV about here]`

The empirical results from an analysis assuming common and heterogeneous technology are contained in Tables III and IV respectively. In all the pooled models we reject homogeneity along the two dimensions investigated (sectors, countries),[6] whereas the heterogeneous models indicate that heterogeneity is pre-dominant across sectors, with countries being made up of heterogeneous sectors seemingly not differing too much from each other. It is evident from the pooled model results that data properties and assumptions about them play an important role in the empirical estimation: in contrast to the results for the micro data, where different pooled estimators for the same dataset yielded similar results the macro results provide powerful evidence of the impact of technology heterogeneity, variable nonstationarity and cross-section dependence if these are unaccounted for. In Figure II we show that once we allow for country-sector specific technology coefficients there is substantial technology heterogeneity in the sample, exemplified here by the scatter plot of the implied labour against the materials coefficients. Figure III plots the same coefficients for a subset of industrial divisions. Further analysis regarding the patterns found in the micro data (richer countries are less material-intensive) will need to be carried out, although initial analysis suggests that this result does not hold in the macro data.

We draw the following first conclusions from this exercise:

1. Parameter heterogeneity across sectors exists and is important.
2. At first glance we cannot find similar patterns to the micro data with reference to the link between income level and materials coefficients.

The following analysis needs to be carried out for the macro data:

[6] Result for CCEP is pending.

- Given the obsession of the empirical literature with TFP, it needs to be pointed out that TFP comparisons are difficult once countries/sectors differ in their technology parameters (see Eberhardt & Teal, 2010, for details). If a way can be found (suggestions such as by Bernard and Jones (1996a) and Eberhardt and Teal (2010) can be considered here) then it would still be meaningful to indicate the contribution of factor inputs versus TFP to growth and development.
- Related to this it would be desirable to show how things go awry if a VA production function with $\beta_K^{va} = .33$ is assumed/imposed.
- A decomposition exercise could assign the share of variation to one of TFP differences, factor input differences and parameter differences, although the parameter estimates are pretty noisy (see next point).
- The estimates are much less precise in the macro data given the limited degrees of freedom afforded the empirical model; most results are therefore meaningful when reported as averages (across all country-sectors, countries or sectors). Still, it would be meaningful and desirable to develop an analogy to the development-material use finding in the micro data (i.e. to either confirm or reject it and in the latter case come up with reasons why).

5. DISCUSSION

[to follow]

6. CONCLUSIONS

[to follow]

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Table I: Cobb-Douglas production functions for firms in Ghana & Korea

	Ghana			Korea		
	[1] **OLS**	[2] **FE**	[3] **GMM**	[4] **OLS**	[5] **FE**	[6] **GMM**
ln$K$	0.035	0.026	0.051	0.110	0.084	0.162
	[0.012]***	[0.010]**	[0.021]**	[0.028]***	[0.025]***	[0.084]
ln$H$	0.129	0.183	0.133	0.414	0.465	0.347
	[0.014]***	[0.013]***	[0.025]***	[0.037]***	[0.037]***	[0.091]***
ln$I$	0.184	0.150	0.154	0.225	0.200	0.148
	[0.018]***	[0.010]***	[0.023]***	[0.030]***	[0.025]***	[0.061]**
ln$M$	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]
TechDiff†: p-value				.000	.000	.009
CRS: p-value	.079	.000	.667	.316	.000	.171
edu: p-value	.009		.049	.000		.000
AR(1): p-value			.000			.482
AR(2): p-value			.000			
AR(3): p-value			.455			
Sargan: p-value			.503			.571
Implied VA $\hat{\beta}_K$	0.213	0.125	0.253	0.209	0.152	0.318
	[0.062]***	[0.048]***	[0.106]**	[0.049]***	[0.045]***	[0.153]**
Implied VA $\hat{\beta}_L$‡	0.787	0.875	0.747	0.791	0.848	0.682
	[0.062]***	[0.048]***	[0.106]***	[0.049]***	[0.045]***	[0.153]***
Observations	1880	1880	1880	918	918	918
Firms		254	254		357	357
RMSE	.390	.310	.060	.506	.207	.036

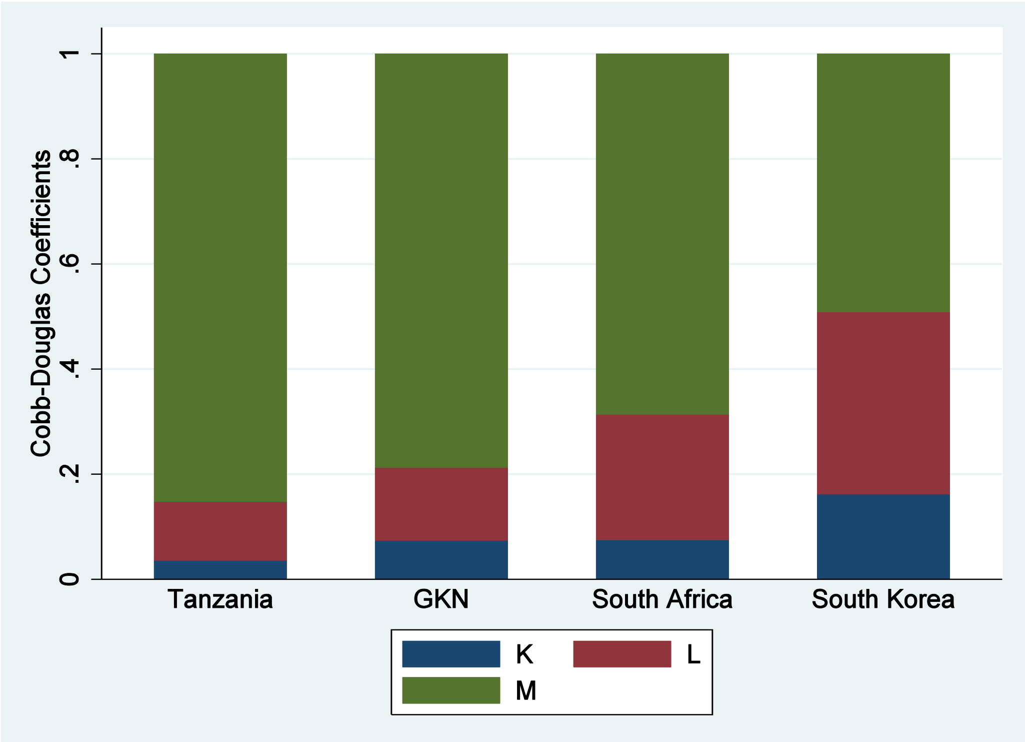
Notes: Production functions in 1996 $PPP for Ghana and South Korea with education included as a quadratic effect. Standard errors in parentheses. H represents weekly man-hours. Constant returns to scale in K, H, I and M have been imposed and CRS is the p-value from a Wald test of this hypothesis. Edu is a Wald test of the null hypothesis that both education coefficients are zero. The autocorrelation test for the system GMM estimates cannot reject AR(2) for Ghana so we take the '$t-3$' and '$t-4$' lags as instruments using the restriction suggested by Bowsher (2002). AR(1) 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 it is not possible to reject the null that the constant terms are equal across countries. † These test the null of technology homogeneity between the South Korean and Tanzanian firms for each empirical model. We also tested for technology homogeneity of factor inputs and TFP (period dummies) separately, rejecting homogeneity in each case. ‡ Since CRS is imposed (given the test results) the standard errors for the implied VA $\hat{\beta}_L$ are the same as for the capital ones (nonlinear combinations of coefficients on ln$K$, ln$I$ and ln$M$ using the variance-covariance matrix for standard error computation via the Delta method).

Table II: Cobb-Douglas production functions in 5 African countries

OLS	[1] Tanzania	[2] GKN	[3] S Africa
ln$K$	0.036	0.074	0.075
	[0.010]***	[0.009]***	[0.020]***
ln$L$	0.112	0.139	0.239
	[0.013]***	[0.016]***	[0.035]***
ln$I$	0.267	0.180	0.132
	[0.025]***	[0.015]***	[0.029]***
ln$M$	0.585	0.607	0.555
	[0.021]***	[0.025]***	[0.039]***
Constant	2.153	2.300	3.466
	[0.107]***	[0.176]***	[0.372]***
Country dummies			
Kenya		-0.069	
		[0.045]	
Nigeria		0.040	
		[0.053]	
Firm characteristics			
Exports	0.032	0.079	0.098
	[0.041]	[0.032]*	[0.052]
Anyfor	-0.028	0.038	0.109
	[0.042]	[0.037]	[0.042]**
Firm Age	-0.001	0.002	0.000
	[0.001]	[0.001]	[0.002]
MetalMac	-0.054	-0.030	0.081
	[0.039]	[0.046]	[0.093]
Textile†	-0.100	-0.127	-0.047
	[0.046]*	[0.061]*	[0.124]
Garments	-0.070	0.001	
	[0.052]	[0.055]	
Wood	0.015	-0.082	
	[0.064]	[0.069]	
Furniture	-0.071	0.011	0.091
	[0.048]	[0.058]	[0.108]
TechDiff: p-value	.002	.590	.048
CRS: p-value	.215	.782	.385
Implied VA $\hat{\beta}_K$	0.244	.348	.238
	[0.058]***	[0.032]***	[0.059]***
Implied VA $\hat{\beta}_L$‡	0.756	0.652	.761
	[0.058]***	[0.032]***	[0.059]***
Observations	721	2,684	260
Firms	302	700	147
RMSE	.278	.400	.264

Notes: Constant returns to scale have been imposed and the p-value testing this from the unrestricted regression is given as CRS. Food and Bakeries is the omitted sector, and Ghana is the omitted country dummy. Year dummies were included but are not reported. TechDiff is a p-value from a test of technological difference: for GKN the null is no difference from each other, for Tanzania and South Africa it is no difference from GKN. The symbols */**/*** identify estimates significantly different from zero at p=0.05/0.01/0.001 respectively. † In S African sample: Textile & Garments. ‡ Since CRS is imposed (given the test results) the standard errors for the implied VA $\hat{\beta}_L$ are the same as for the capital ones (nonlinear combinations of coefficients on ln$K$, ln$I$ and ln$M$ using the variance-covariance matrix for standard error computation via the Delta method).

Figure I: Cross-country technology comparison



Notes: Chart summarising the information on technology contained in Tables I and II. The output elasticities for materials and indirect costs have been combined.

Table III: Pooled Cobb-Douglas production functions for sectoral data

	[1] **POLS**	[2] **POLS**	[3] **POLS**	[4] **2FE**	[5] **CCEP**	[6] **FD**
ln$K$	0.115	0.093	0.109	0.146	0.091	0.076
	[0.004]***	[0.003]***	[0.004]***	[0.003]***	[0.005]***	[0.007]***
ln$L$	0.049	0.071	0.093	0.061	0.109	0.138
	[0.003]***	[0.003]***	[0.006]***	[0.003]***	[0.005]***	[0.006]***
ln$M$	0.821	0.801	0.780	0.797	0.818	0.797
	[0.003]***	[0.003]**	[0.005]***	[0.003]***	[0.004]***	[0.004]***
E	0.003	0.001	-0.013	-0.023	-0.018	0.013
	[0.004]	[0.008]	[0.007]*	[0.004]***	[0.011]*	[0.017]
E^2	0.002	0.000	0.001	0.001	0.001	-0.001
	[0.000]***	[0.001]	[0.000]	[0.000]***	[0.001]	[0.001]
Constant	1.243			1.152		
	[0.024]***			[0.048]***		
TechDiff(i): p-value	.000	.000	.000	.000	.000	.000
TechDiff(ii): p-value	.000	.000	.000	.000	.000	.000
CRS: p-value	.000	.000	.000	.110	.000	.180
edu: p-value	.000	.600	.150	.000	.207	.670
Implied VA $\hat{\beta}_K$	0.643	0.468	0.497	0.721	0.500	0.371
	[0.013]***	[0.012]***	[0.017]***	[0.015]***	[0.028]***	[0.035]***
Implied VA $\hat{\beta}_L$	0.275	0.358	0.421	0.300	0.598	0.677
	[0.016]***	[0.017]***	[0.023]***	[0.016]***	[0.025]***	[0.026]***
Residuals	I(1)	I(1)	I(1)	I(1)	I(0)	I(0)
Observations	12,878	12,878	12,878	12,878	12,878	11,349
RMSE	.201	.170	.136	.078	.055	.051
year FE	yes	yes	yes	yes	no	yes
country FE	no	yes	yes	no	no	no
sector FE	no	no	yes	no	no	no
country-sector FE	no	no	no	yes	yes	no

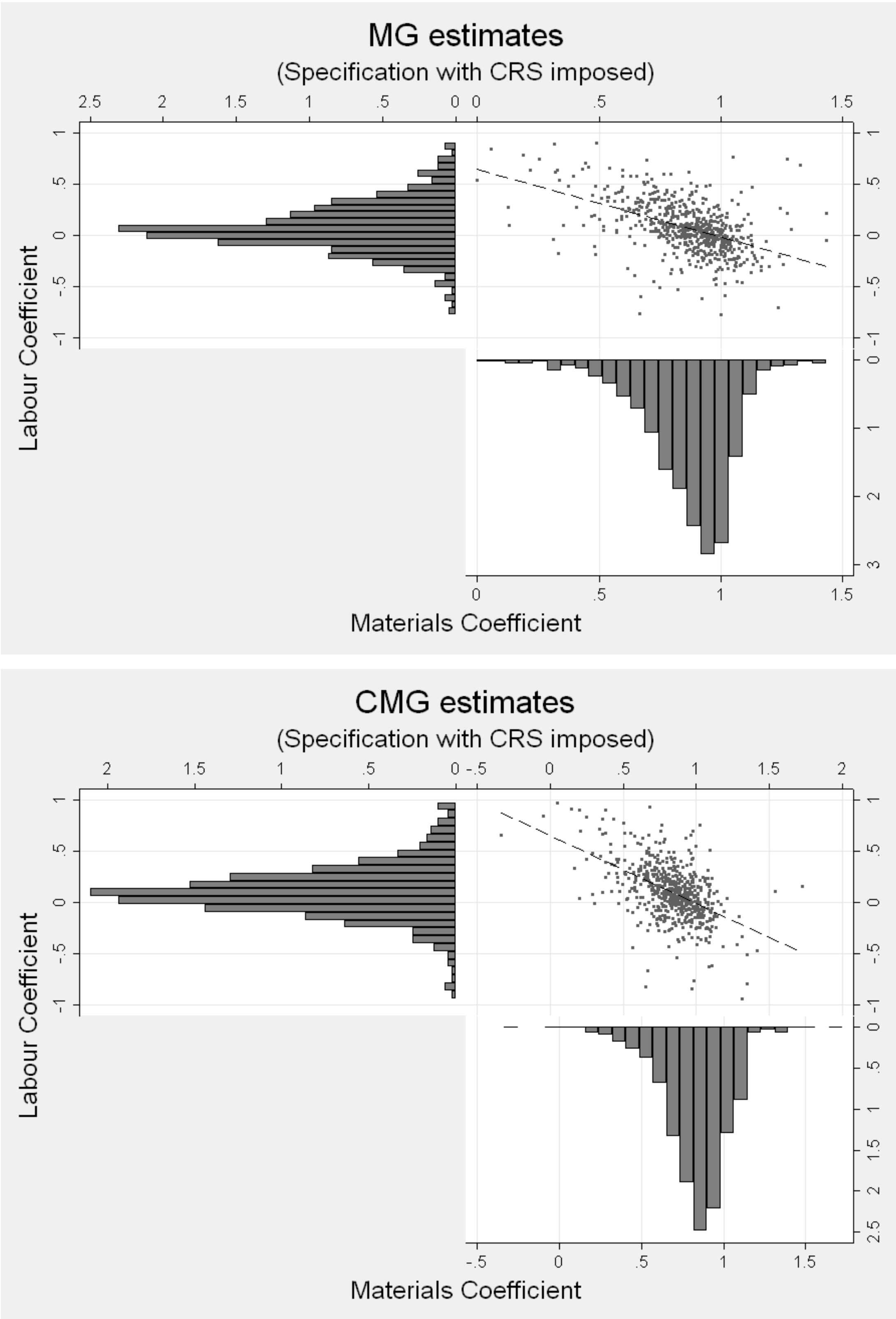
Notes: Results for $n = 12,878$ (FD: $n = 11,349$) observations in 639 sectors of $N = 50$ countries. Dependent variable: gross-output (in logs). All variables are suitably transformed in the FD equations. Estimators: POLS — pooled OLS (additional fixed effects as indicated), 2FE — 2-way Fixed Effects (time and country-sector fixed effects), CCEP — Common Correlated Effects (pooled version), FD — pooled OLS with variables in first difference. We omit reporting the estimates on the cross-section averages (in model [5]). TechDiff(i) tests the null of technology homogeneity across sectors and TechDiff(ii) across countries. The Wald test for constant returns to scale has the null of CRS. Standard errors reported in brackets are constructed using the White heteroskedasticity-robust method. *, ** and *** indicate significance at 10%, 5% and 1% level respectively. x — to be added. Note that the CCEP estimates and heterogeneity tests were run in Stata 10 MP with 1GB memory, using `xtregfast` by Johannes Schmieder at Columbia University.

Table IV: Heterogeneous Cobb-Douglas production functions for sectoral data

	[1] **MG**	[2] **CDMG**	[3] **CMG**
ln$K$	0.052	0.088	0.062
	[0.007]***	[0.007]***	[0.008]***
ln$L$	0.059	0.066	0.090
	[0.010]***	[0.009]***	[0.011]***
ln$M$	0.889	0.845	0.848
	[0.006]***	[0.006]***	[0.007]***
E	0.199	-0.063	-0.169
	[0.119]*	[0.013]***	[0.083]**
E^2	-0.010	0.005	0.014
	[0.007]	[0.001]***	[0.006]**
Constant	1.236	-0.006	0.987
	[0.442]***	[0.012]	[0.402]**
TechDiff(i): p-value	.000	.000	.000
TechDiff(ii): p-value	.641	.148	.993
CRS: p-value	.000	.374	.194
Edu: p-value	.090	.000	.012
Implied VA $\hat{\beta}_K$	0.472	0.570	0.406
	[0.071]***	[0.048]***	[0.056]***
Implied VA $\hat{\beta}_L$‡	0.528	0.430	0.594
	[0.071]***	[0.048]***	[0.056]***
Residuals	I(0)	I(0)	I(0)
Observations	12,878	12,878	12,878
RMSE	0.039	0.047	0.030

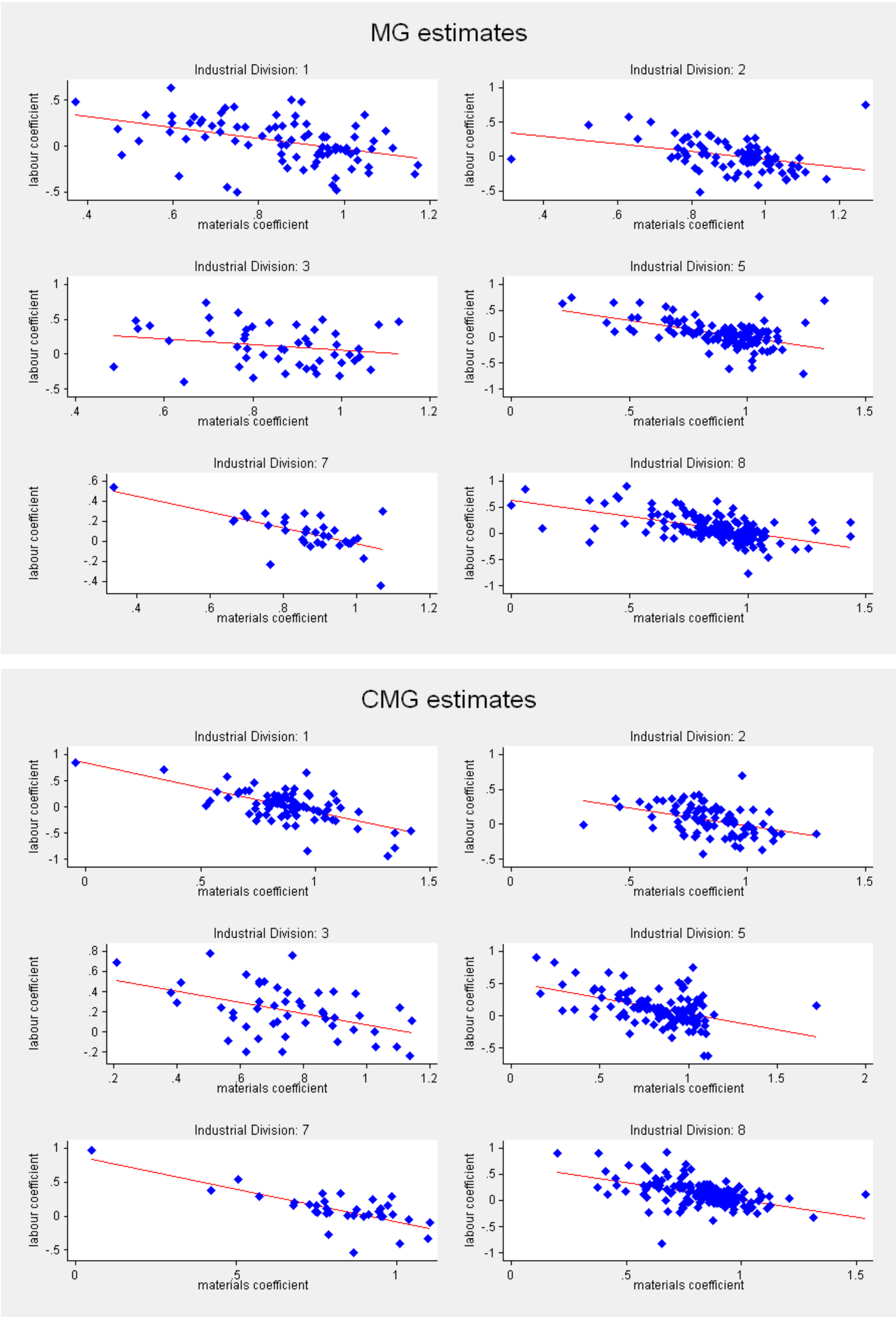
Notes: Results for $n = 12,878$ observations in 639 sectors of $N = 50$ countries. Dependent variable: gross-output (in logs). All variables are suitably transformed in the CDMG equations. Estimators: MG — Pesaran and Smith (1995) Mean Group, augmented with a country-sector specific linear trend (30% of trends are significant at the 5% level), CDMG — Mean Group with variables in deviation from the cross-section mean, CMG — Pesaran (2006) CCE estimator, Mean Group version. We report the robust mean of coefficients across countries (Hamilton, 1992); standard errors are constructed following Pesaran and Smith (1995). *, ** and *** indicate significance at 10%, 5% and 1% level respectively. ‡ Since CRS is imposed (given the test results) the standard errors for the implied VA $\hat{\beta}_L$ are the same as for the capital ones (nonlinear combinations of coefficients on ln$K$, ln$l$ and ln$M$ using the variance-covariance matrix for standard error computation via the Delta method).

Figure II: Country-sector specific coefficients



Notes: Each scatter plots the implied labour coefficients (CRS imposed) against the estimated materials coefficients. The histogram in the top left (bottom right) corner then portrays the distribution of the labour (materials) coefficients.

Figure III: Country-sector specific coefficients: Division plots



Notes: y-axis – labour-coefficient; x-axis – materials-coefficient. These are the coefficients underlying the average result presented in Table IV. Red lines are fitted least squares regression lines. The divisions presented are: 1 – Food & Tobacco, 2 – Textile & Clothing, 3 – Wood, 5 – Chemicals, 7 – Basic Metals, 8 – Machinery.

DATA APPENDIX

A-1 Data construction and descriptives — Micro data

The data used in the first set of empirical results is taken from a balanced panel of 863 South Korean manufacturing firms observed for three years and an unbalanced panel of 312 Ghanaian manufacturing firms observed for twelve years. For the production function regressions we could use samples of 357 firms (918 observations) and 250 firms (1,880 observations) for South Korea and Ghana, respectively. Descriptive statistics are provided in Table A-I below.

Table A-I: Descriptive statistics (i)

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)	
Weekly man-hours (H)	3,297	997	5,659	3,842
	(7,410)		(5,861)	
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)	
VA/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	254		357	
Observations	1880		918	

Notes: Descriptive Statistics for variables used in estimation. The monetary values are expressed as '000 1996 $PPP. Standard errors are in parenthesis. H is calculated as L*Hours. VA refers to value-added.

The Ghanaian data was collected in a series of interviews with firm management and cover the period 1991-2002.[7] 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 dataset (including definitions and variable construction) is the same used in Söderbom and Teal (2004) with the addition of a 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. Other production variables are: the value of physical capital stock; the number of employees; and the expenditure on materials, electricity, other energy, and rent. 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 data set 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.

If we wish to compare TFP across economies, it is imperative to use units that are as comparable across countries as possible, and so the deflation procedure is important. Output, capital, raw material and indirect costs are all in 1996 PPP$, while the labour force is measured as number of employees adjusted by hours worked and education is the average number of years of schooling of employees of the firm. The deflation procedure used was to deflate the nominal values into constant price domestic values using firm specific price indices and then convert into PPP$ using the exchange rates in the Penn World Tables 6.1 (Heston, Summers, & Aten, 2002). The PPP investment deflator was used for the capital stock, the consumption deflator for indirect and material inputs, and the GDP deflator for output. Firms were asked to report the annual percentage change in output and intermediate input prices for each year. From this, an index of firm specific output and material input prices was constructed.

In our second set of results we employ firm-level data for a number of African countries. Table A-III summarises the pooled unbalanced panel on manufacturing firms from five countries, which were collected as part of the RPED as described above (footnote A-1). The data deflation and variable construction are as described for Ghana with three exceptions. In Kenya the price indices were sector specific rather than firm specific. In the cases of Nigeria and South Africa the nominal values were deflated by consumer prices, producer prices being unavailable, and then converted into US$ using the exchange rate for the base period. These US$ numbers were then deflated by the PPP deflator to 1996 values. The firms are classified into seven sectors: food/bakery, metals/machinery/chemical/paper,

[7]The were collected by a team from the Centre for the Study of African Economies, Oxford, the University of Ghana, Legon and the Ghana Statistical Office (GSO), Accra over a period from 1992 to 2003. We are greatly indebted to staff from the GSO for their assistance. The surveys from 1992 to 1994 were part of the Regional Program on Enterprise Development (RPED) organised by the World Bank. The surveys have been funded by the Department for International Development of the UK government. The Kenyan, Nigerian and Tanzanian data collection was funded by both DFID and UNIDO. Work on this project was funded by the Economic and Social Research Council of the UK as part of the Global Poverty Research Group.

textiles, garments, wood, furniture, and a sector consisting of South African textile and garment firms. The variable definitions are taken from Rankin, Söderbom, and Teal (2006). Employment is the total number of employees in the firm. Output, capital, raw material and indirect costs are all in 1996 PPP$. The deflation procedure used for Ghana, Kenya and Tanzania was to deflate the nominal values into constant price domestic and then convert into PPP$ using the exchange rates in the Penn World Tables. The deflation for both Ghana and Tanzania used firm based price indices while for Kenya sector level deflators were used. In the case of Nigeria and South Africa, the nominal values were deflated by consumer prices (producer prices being unavailable) then converted in US$ using the exchange rate for the base period. These US numbers were then deflated by the PPP deflator to 1996 values. Firm age is in years and any foreign ownership is a dummy which takes the value 1 if the firm has any element of foreign ownership and zero otherwise. Exports is a dummy taking the value 1 if the firm exports, and Educ is the weighted average of years of education of workers in the firm. The Nigerian data in Malik, Teal, and Baptist (2006). Most of this data is available at www.csae.ox.ac.uk. Below summary statistics were calculated over those observations with data on all variables and so those regressions without the full set of variables may include some additional observations.

Table A-II: Descriptive statistics (ii)

	Tanzania	GKN	Ghana	Kenya	Nigeria	S Africa
ln$Y$	12.03	12.92	12.24	13.80	13.66	16.21
	(2.37)	(2.48)	(2.22)	(2.36)	(2.71)	(1.21)
ln$K$	11.19	11.89	10.97	13.30	12.58	15.18
	(3.08)	(3.18)	(2.99)	(2.90)	(3.19)	(1.65)
ln$L$	2.89	3.29	3.13	3.50	3.44	4.86
	(1.54)	(1.56)	(1.43)	(1.64)	(1.74)	(0.87)
ln$M$	11.25	12.12	11.42	13.01	12.88	15.38
	(2.48)	(2.57)	(2.22)	(2.51)	(2.94)	(1.35)
Anyfor	0.15	0.18	0.18	0.19	0.20	0.25
	(0.35)	(0.39)	(0.38)	(0.39)	(0.40)	(0.43)
Exports	0.14	0.20	0.17	0.35	0.08	0.65
	(0.35)	(0.40)	(0.37)	(0.48)	(0.28)	(0.48)
Firm Age	15.32	19.50	17.96	20.79	22.03	19.87
	(11.94)	(12.24)	(11.90)	(13.36)	(10.98)	(16.77)
Observations (N)	721	2,684	1,458	691	535	260
Firms	302	700	226	320	154	147

Notes: GKN refers to the pooled sample for Ghana, Kenya and Nigeria. The monetary values are expressed as '000 1996 $PPP. Standard errors are in parenthesis, this can be converted into the standard deviation of the variable through multiplying by $\sqrt{N}$.

A-2 Data construction and descriptives — Macro data

The data for the macro production function regressions is taken from the World Bank's 'Trade, Production and Protection' dataset compiled by Nicita and Olarreaga (2007). The data aggregates and merges production data for 28 manufacturing sectors from UNIDO with trade data for the relevant sectors from UN COMTRADE. The monetary values in this dataset are in current 1,000 US$, so we apply the US GDP deflator to transform them into real/constant values (see Schiff et al for confirmation that variables are in current US$; this was also confirmed by Alessandro Nicita). We employ a number of standard data cleaning rules based on the investment-capital and capital-output ratios to weed out misreported values. Capital stock is created using the Perpetual Inventory Method (PIM), applying a depreciation rate of 5% per annum across all sectors and using the standard trick to obtain base year capital stock as described in Klenow and Rodriguez-Clare (1997). We dropped all country-sectors which did not have in excess of nine observations for investment. The resulting sample comprises 50 developing and developed countries with a total of 12,878 observations in 639 sectors (average number of observations per sector: 18.6) for 1976-2002. The panel is unbalanced in two senses: firstly, given the differential structural makeup of economies we have countries with data for up to 26 sectors and others with data for merely 1 sector. Secondly, within the given sector structure we miss about 25% of the observations to create a balanced panel for 639 sectors. Coverage in each year exceeds 70% until the mid-1990s, then drops to around 60% in the late 1990s and finally 26% and 10% for 2001 and 2002 respectively. In terms of geographical coverage we note that with Ethiopia we have only one country from Sub-Saharan Africa, where the manufacturing sector is generally small in comparison to other LDCs with similar per capita income.

We provide descriptive statistics for the macro production function variables in Table A-III and detail the sectoral and country makeup of the sample in Tables A-IV to A-V.

Table A-III: Descriptive statistics

Panel (A): Variables in untransformed level terms

Variable	**mean**	**median**	**std. dev.**	**min.**	**max.**
untransformed					
Output	1.22E+10	1.26E+09	4.01E+10	49,920	5.28E+11
Value-added	4.92E+09	4.50E+08	1.70E+10	19,967	2.09E+11
Labour	99,710	21,103	241,006	1	2,518,000
Capital	6.55E+09	6.82E+08	2.07E+10	14,174	2.47E+11
Materials	7.26E+09	7.69E+08	2.42E+10	29,953	3.19E+11
in logarithms					
Output	20.947	20.956	2.278	10.818	26.992
Value-added	19.932	19.925	2.283	9.902	26.065
Labour	9.892	9.957	1.944	0.000	14.739
Capital	20.311	20.341	2.337	9.559	26.234
Materials	20.441	20.461	2.303	10.307	26.488
in growth rates					
Output	4.08%	3.66%	15.68%	-69.46%	88.81%
Value-added	3.84%	3.22%	17.96%	-70.84%	112.22%
Labour	1.27%	0.45%	9.75%	-36.24%	69.31%
Capital	4.20%	2.72%	7.41%	-41.05%	96.13%
Materials	4.21%	3.52%	16.88%	-73.05%	96.53%

Panel (B): Variables in per workers terms

Variable	**mean**	**median**	**std. dev.**	**min.**	**max.**
untransformed					
Output	114,196	65,524	224,186	2,198	3,684,087
Value-added	39,225	25,073	67,246	579	1,364,537
Capital	58,518	35,071	90,811	537	1,449,933
Materials	74,971	38,671	180,815	1,259	3,388,888
in logarithms					
Output	11.055	11.090	1.002	7.695	15.120
Value-added	10.039	10.130	1.017	6.361	14.126
Capital	10.419	10.465	1.066	6.286	14.187
Materials	10.549	10.563	1.029	7.138	15.036
in growth rates					
Output	2.82%	2.67%	13.32%	-47.34%	77.50%
Value-added	2.58%	2.31%	15.92%	-59.72%	61.17%
Capital	2.91%	2.77%	9.93%	-39.82%	42.84%
Materials	2.94%	2.74%	14.69%	-48.35%	56.38%

Panel (C): Education variables‡

Variable	**mean**	**median**	**std. dev.**	**min.**	**max.**
Education	6.80	6.54	2.36	0.84	12.14
Education^2	51.82	42.77	34.02	0.70	147.38

Notes: We report the descriptive statistics for value-added and gross-output (both in US$1990), labour (headcount), capital stock (in US$1990) and material inputs (in US$1990) for the full regression sample ($n = 12,868$; $N = 50$ countries). ‡ Education refers to national average years of schooling (taken from the 'urban' estimates reported in Timmer (2002) and supplemented with interpolated data from Caselli, Mayer and Wood (2010), which is itself based on the Barro and Lee (2001) data).

Table A-IV: Macro dataset: Sectoral makeup

Division	**ISIC**	**Sector description**	**Obs**	**Share**	**N**
Food &	311	Food products	869	6.8 %	42
Tobacco	313	Beverages	358	2.8 %	18
	314	Tobacco	505	3.9 %	27
Textile &	321	Textiles	335	2.6 %	19
Clothing	322	Wearing apparel except footwear	630	4.9 %	29
	323	Leather products	460	3.6 %	22
	324	Footwear except rubber or plastic	353	2.7 %	17
Wood	331	Wood products except furniture	399	3.1 %	19
	332	Furniture except metal	602	4.7 %	29
Paper	341	Paper and products	572	4.4 %	30
	342	Printing and publishing	584	4.5 %	28
Chemicals	351	Industrial chemicals	276	2.1 %	15
	352	Other chemicals	673	5.2 %	33
	353	Petroleum refineries	239	1.9 %	12
	354	Miscellaneous petroleum and coal produc	199	1.6 %	11
	355	Rubber products	394	3.1 %	19
	356	Plastic products	601	4.7 %	30
Non-metals	361	Pottery china earthenware	38	0.3 %	2
	362	Glass and products	122	1.0 %	7
	369	Other non-metallic mineral products	271	2.1 %	14
Basic	371	Iron and steel	299	2.3 %	16
Metals	372	Non-ferrous metals	407	3.2 %	19
Machinery	381	Fabricated metal products	620	4.8 %	30
	382	Machinery except electrical	655	5.1 %	32
	383	Machinery electric	696	5.4 %	34
	384	Transport equipment	592	4.6 %	30
	385	Professional and scientific equipment	551	4.3 %	27
Other	390	Other manufactured products	578	4.5 %	28
		Full Sample	12,878		

Notes: The Division labels are the ones applied throughout the paper. ISIC refers to the Revision 2 code for the manufacturing subsector. Obs indicates the number of observations within each sector, Share the proportion of the full sample, N the number of countries for which data is available in the respective sector.

Table A-V: Macro dataset: Country makeup

wbcode	Country	Obs	Share	# sectors	$\bar{T}$/sector
AUS	Australia	176	1.4 %	10	17.6
AUT	Austria	495	3.8 %	23	21.5
BGD	Bangladesh	52	0.4 %	4	13.0
BOL	Bolivia	77	0.6 %	5	15.4
CAN	Canada	250	1.9 %	17	14.7
CHL	Chile	356	2.8 %	18	19.8
CMR	Comores	13	0.1 %	1	13.0
COL	Colombia	533	4.1 %	22	24.2
CYP	Cyprus	477	3.7 %	20	23.9
DNK	Denmark	231	1.8 %	15	15.4
ECU	Ecuador	20	0.2 %	1	20.0
EGY	Egypt	43	0.3 %	3	14.3
ESP	Spain	592	4.6 %	26	22.8
ETH	Ethiopia	211	1.6 %	10	21.1
FIN	Finland	316	2.5 %	15	21.1
FRA	France	91	0.7 %	5	18.2
GBR	United Kingdom	446	3.5 %	19	23.5
GRC	Greece	254	2.0 %	14	18.1
GTM	Guatemala	13	0.1 %	1	13.0
HKG	Hong Kong	256	2.0 %	11	23.3
IDN	Indonesia	257	2.0 %	13	19.8
IND	India	404	3.1 %	16	25.3
IRL	Ireland	235	1.8 %	15	15.7
IRN	Iran	190	1.5 %	12	15.8
ISR	Israel	203	1.6 %	10	20.3
ITA	Italy	372	2.9 %	17	21.9
JPN	Japan	631	4.9 %	26	24.3
KOR	Korea, Republic of	542	4.2 %	24	22.6
KWT	Kuwait	134	1.0 %	7	19.1
LKA	Sri Lanka	59	0.5 %	4	14.8
MAC	Macao	210	1.6 %	11	19.1
MAR	Morocco	112	0.9 %	7	16.0
MEX	Mexico	371	2.9 %	20	18.6
MLT	Malta	411	3.2 %	20	20.6
MYS	Malaysia	342	2.7 %	17	20.1
NLD	Netherlands	115	0.9 %	7	16.4
NOR	Norway	276	2.1 %	13	21.2
NZL	New Zealand	169	1.3 %	12	14.1
PAK	Pakistan	52	0.4 %	4	13.0
PAN	Panama	133	1.0 %	8	16.6
PER	Peru	67	0.5 %	5	13.4
PHL	Philippines	337	2.6 %	21	16.0
PRT	Portugal	444	3.5 %	21	21.1
SGP	Singapore	468	3.6 %	20	23.4
TTO	Trinidad and Tobago	40	0.3 %	3	13.3
TUN	Tunisia	179	1.4 %	10	17.9
TUR	Turkey	551	4.3 %	25	22.0
URY	Uruguay	70	0.5 %	5	14.0
USA	United States	557	4.3 %	23	24.2
VEN	Venezuela	45	0.4 %	3	15.0
	Full Sample	12,878		639	$\bar{T} = 18.6$

Notes: We report the number of sectors for which each country has data and the average sector-level observations.