

TECHNOLOGY, HUMAN CAPITAL AND EFFICIENCY IN MANUFACTURING FIRMS

SIMON BAPTIST
NEW COLLEGE
UNIVERSITY OF OXFORD

A THESIS SUBMITTED FOR THE
DEGREE OF
DOCTOR OF PHILOSOPHY
AT THE UNIVERSITY OF OXFORD
TRINITY TERM 2008

Contents

1	Introduction	2
2	Sources of Productivity Difference	14
2.1	Introduction	15
2.2	Scale, Skills and Technology	19
2.3	Productivity in Ghanaian and South Korean Firms	27
2.4	Estimating Technology and the Return to Skills	34
2.5	Some Robustness Checks	48
2.6	Why Does Productivity Differ?	54
2.7	Concluding Remarks	60
2.A	Data Appendix	62
2.B	Value Added vs Gross Output Production Functions	65
2.C	Dynamics and the System GMM Estimator	67
3	Technological Change in Africa	84
3.1	Introduction	85
3.2	A Global Model of Technology	86
3.3	Technology Across the Continent	88
3.3.1	Heterogeneity Within Africa	90
3.3.2	Skills	93
3.4	A More General Specification	96
3.4.1	The Translog Production Function	96
3.4.2	Results	101
3.5	Understanding Technology	112
3.5.1	Technology Across Countries	116
3.5.2	Materials and Risk	118
3.6	Concluding Remarks	124
3.A	Elasticities of Substitution	126

4	Skills and Human Capital in Earnings and Production Functions	131
4.1	Introduction	132
4.2	Modelling Skills and Human Capital	137
4.3	Data	146
4.4	Skills in the Production Function	158
	4.4.1 Skills in a CES Production Function	158
	4.4.2 Skills in a Cobb-Douglas Production Function	162
4.5	Earnings Functions	166
	4.5.1 Estimating Earnings Functions	166
	4.5.2 Results	179
4.6	Wage and Productivity Premiums	204
4.7	Concluding Remarks	205
4.A	Unabridged Earnings Functions	208
5	Conclusions	215

List of Figures

2.1	GDP per Capita in Ghana and South Korea	16
2.2	TFP and Education for Ghanaian and South Korean Firms. . .	44
2.3	Value Added vs Capital: Ghana and South Korea	59
3.1	Returns to Scale vs Employment in Tanzania	111
4.1	Earnings of Skilled Workers	184
4.2	Earnings of Unskilled Workers	185
4.3	The Return to Education for Ghanaian Workers	188
4.4	Effect of Education on Selection into Occupation	197
4.5	Firm Fixed Effects by Skill Type	202
5.1	The Pattern of Cross-Country Technology	218

List of Tables

2.1	Descriptive Statistics for Ghanaian and South Korean Firms .	33
2.2	Production Functions: Ghana and South Korea(a)	38
2.3	Production Functions: Ghana and South Korea(b)	39
2.4	Production Functions: Ghana and South Korea(c)	40
2.5	Value Added Production Functions: Ghana and South Korea .	41
2.6	Robustness Checks for Table 2.2	42
2.7	Additional Robustness Checks for Table 2.2	43
2.8	Macro and Micro Growth Accounting	54
2.9	Dynamic CRS Production Function: South Korea	81
2.10	Dynamic CRS Production Function: Ghana	82
2.11	Implied Long-run Dynamic Coefficients: South Korea	83
2.12	Implied Long-run Dynamic Coefficients: Ghana	83
3.1	Summary Statistics for African Data	91
3.2	Production Functions Across Africa	92
3.3	Production Functions Across Africa with Education	95
3.4	African Translog Production Functions(a)	102
3.5	African Translog Production Functions(b)	103
3.6	African Translog Output Elasticities	106
3.7	Translog Specification Tests	107
4.1	Variables Used in the Earnings Functions(a)	154
4.2	Variables Used in the Earnings Functions(b)	155
4.3	Variables Used in the Earnings Functions(c)	156
4.4	Years of Education of Skilled and Unskilled Workers	157
4.5	Descriptive Statistics for the CES Data	159
4.6	CES Production Function for Ghana	161
4.7	Output Elasticities from the CES Production Function	162
4.8	Production Function with Skills: Ghana and South Korea . . .	163
4.9	Earnings Functions for Ghana	180
4.10	Earnings Functions for Ghana without Firm Controls	181
4.11	Selection into Skilled Occupations(a)	182

4.12	Selection into Skilled Occupations(b)	183
4.13	Earnings Functions for Ghana: OLS and Heckman(a)	209
4.14	Earnings Functions for Ghana: OLS and Heckman(b)	210
4.15	Earnings Functions for Ghana: OLS and Heckman(c)	211
4.16	Earnings Functions for Ghana: IV(a)	212
4.17	Earnings Functions for Ghana: IV(b)	213
4.18	Earnings Functions for Ghana: IV(c)	214

Acknowledgements

The most important thanks are due to my supervisor, Dr. Francis Teal. He has been engaged and interested in my work throughout the course of the M.Phil. and D.Phil. and provided much valuable feedback. I have also benefited greatly from discussing the issues raised in this thesis with Måns Söderbom, Markus Eberhardt and Courtney Monk. Quality data is critical for empirical work, and I am appreciative to the CSAE and the World Bank for collecting and making it available. The University of Tasmania and the Oxford-Australia Trust provided valuable financial support. Finally I would like to thank my mother, Miranda, and my partner, Justinian Habner, for their longstanding support and encouragement of my academic pursuits.

Word Count

The body of this thesis contains 221 pages, with a typical page containing around 285 words, making the length of the document approximately 63,000 words.

TECHNOLOGY, HUMAN CAPITAL AND EFFICIENCY IN MANUFACTURING FIRMS
SIMON BAPTIST
NEW COLLEGE, UNIVERSITY OF OXFORD
DOCTOR OF PHILOSOPHY IN ECONOMICS
TRINITY TERM 2008

Abstract

Accounting for output per worker differences across countries has been an ongoing topic of research in economics. This thesis expands upon standard approaches by allowing for technological heterogeneity and exploiting firm and worker level data to determine the microeconomic sources of variation in both productivity and earnings.

An intercontinental comparison using production functions for the Ghanaian and South Korean manufacturing sectors in Chapter 2 finds, in contrast to the conclusions of much of the macroeconomic literature, that there is no difference in total factor productivity (TFP). The microeconomic sources of the difference in value added per worker lie within the technology of firms, which is defined as the way in which inputs are used. Two important dimensions of this difference are the larger role of material inputs and the much lower rate of return to schooling in Ghana.

In Chapter 3 a more general specification investigates intra-African variation in production, which is much smaller than the intercontinental difference. The pattern of cross-country heterogeneity is that, as GDP per capita rises, the relative input of materials falls, those of capital and labour rise and the returns to education increase. Differences in TFP are limited.

Possible sources of the low returns to schooling in Ghana are investigated in Chapter 4 using earnings and production functions. Conditional upon selection into occupations, the only group of workers for whom education appreciably increases earnings are those employed in skilled jobs with more than ten years of education. The evidence is consistent with a lack of technological sophistication being the source of these low returns.

Investment in new production processes by firms will increase the return to education and raise incomes and output. Reducing the share of intermediate inputs in production is key to the transition from low to high productivity activities. Technology is the critical element that can explain the performance of manufacturing firms across countries.

Chapter 1

Introduction

Accounting for the substantial income differences observed between countries has been an enduring topic of research for the economics profession. This thesis expands upon current approaches to this question by allowing for technological heterogeneity and exploiting firm and worker level data to determine the microeconomic sources of variation. 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:

$$Y_{it} = A_{it}K_{it}^{\beta}L_{it}^{1-\beta}; \quad (1.1)$$

where i and t are subscripts for countries and years respectively, 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 equal to $\frac{1}{3}$ (or a value close to this¹). Differences in output per worker between countries

¹It is this assumption that means that TFP can be calculated without any estimation in such approaches.

and across time can then be attributed to either differences in the amount of capital per worker or differences in TFP, with the relative roles of each the subject of debate. In a comprehensive meta-study, Jorgenson [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. Young [1994] conducts a similar exercise for East Asia and also concludes that factor accumulation is more important than TFP. The opposite conclusion is reached by Easterly and Levine [2001], and much of the cross-country literature similarly finds that inputs are much less important than TFP. Many authors have noted that this is an unsatisfactory explanation as it is only identifying a 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. We will find that accounting for intermediate inputs and technological heterogeneity at the microeconomic level is able to substantially reduce, if not remove, TFP differences between countries at the sectoral level.

Caselli [2005] summarises the puzzle in the cross-country productivity literature as one of inputs having insufficient explanatory power. Relaxing some of the assumptions implicit in Equation 1.1, in an attempt to overcome this puzzle, is the subject of an extensive literature. For example: the measure of L can be augmented with measures of education [Hall and Jones, 1999] or the proportions of skilled and unskilled workers [Caselli and Coleman, 2006]; the Cobb-Douglas functional form can be generalised [Jerzmanowski, 2007]; or value added can be corrected for rents accruing to natural capital [Caselli and Feyrer, 2007]. While the proportion of variation in output per worker at-

tributed to TFP is generally reduced with each generalisation, it still remains significant. Caselli [2005] surveys this literature and concludes that none of these generalisations can satisfactorily explain the wide TFP differentials.

Five possibilities for the lack of explanatory power of inputs in describing global variation in output per worker are investigated in this thesis: the true microeconomic sources are being masked by the aggregation process, estimates are biased from the way intermediate inputs are modelled in the value added specification, technology is being incorrectly assumed to be homogeneous across countries, the Cobb-Douglas functional form is inappropriate, and, finally, alternative approaches to modelling human capital are needed. Adopting a Cobb-Douglas specification for now, the set of country specific production functions for a sector is defined as:

$$\ln Y_{it} = \alpha_{it} + \beta_K^i \ln K_{it} + \beta_L^i \ln L_{it} + \beta_I^i \ln I_{it} + \beta_M^i \ln M_{it} + \phi^i(E_{it}). \quad (1.2)$$

The convex hull of Equation 1.2 over all countries i is then the world technology frontier. Equation 1.2 differs from Equation 1.1 in that it allows the coefficients β and the function ϕ to differ across countries, explicitly includes human capital E , includes material and indirect inputs M and I , and uses gross output rather than value added as the measure of Y . The framework of Equation 1.2 is the basis for the intercontinental comparative analysis between Ghana and South Korea carried out in Chapter 2, and the intra-African analysis of Chapter 3. The analysis of skills in Chapter 4 employs a more generalised production structure allowing occupation and education to have differential effects. The theoretical and empirical background to the

five generalisations of the approach used to explain cross-country differences in output per worker are now discussed in turn.

Firstly, we note that production is a microeconomic process. The microeconomic level will, depending on the precise question, generally be the appropriate one for the analysis of production. It may be that the characteristics of production that can explain cross-country differences are masked through some artefact of the aggregation process. There are now a large number of firm level data sets available for a wide range of countries that have been used to investigate issues of productivity in individual countries [Söderbom and Teal, 2004, Hay, 2001, Chen and Tang, 1987] and, in a more limited way, in groups of similar countries [Hallward-Driemeier et al., 2002, Clerides et al., 1998, Rankin, 2004]. This availability opens up the possibility of making more comprehensive use of the data, in an analogous way to the usual macroeconomic approach, so as to investigate cross-country output per worker differentials. Although some of the factors that are important for productivity at the micro level also show up as important in the macro data, 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.

Chapters 2 and 3 model production using the firm as the unit of analysis, providing an alternative to the sectoral or aggregate approach of the macroeconomic literature. Chapter 4 uses both earnings and production functions to further understand the importance of skills and schooling in manufacturing firms, particularly in Ghana. Human capital is influenced by a number of factors such as natural ability, schooling and work experience. The impact

of these factors on earnings and firm productivity will be explored using a matched firm-worker data set. Qualifications from schooling may act simply as a sorting device, in which case the impact on productivity is limited, or they may create skills which are valuable to firms in the production process. Skills can then, in turn, affect both the productivity and the technology of the firm.

Secondly, the specification used will test for the idea that the TFP differences are an artefact of the value added specification. 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 is calculated as the value of gross output minus the value of intermediate input purchases. A value added production function, implicitly assumed by models such as Equation 1.1, relates inputs of capital and labour to value added. In order for the value added specification to be valid, a number of technical conditions need to be met. These include that capital and labour are jointly separable from other inputs and that technical change is Hicks-neutral [Jorgenson, 1990]. The value added production function will, in general, also give a biased estimate of TFP (see Appendix 2.B for a proof). Value added production functions can be useful in analysing the flow of income to factors, and also where data on intermediate input use and gross output is unavailable. With the availability of comprehensive data sets the need for estimating a value added production function is diminished, as value added measures can be derived following estimation of a gross output production function. One advantage of the gross output function is that it encompasses the value added function, whereas the

converse does not hold.

Of the available cross-country comparisons at the micro level, Eifert et al. [2005], while not including intermediate inputs in the production function, is one of very few to consider the role of intermediate inputs. They argue that high indirect costs are reflective of the poor investment climate in Africa and that ignoring intermediate inputs portrays too narrow a view of firm performance in Africa.

Given the biases from a value added production function, and our wish to test if the way in which inputs are modelled is important, we adopt the gross output specification in this paper. Harrigan [1999] concurs with this view and writes that the gross output production function “is undoubtedly the most theoretically appealing and least restrictive method of making productivity comparisons”, while Jorgenson [1990] says 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.

The third key generalisation made is that the specification will allow for technology to differ across countries. In an intuitive sense, technology describes the way in which inputs are transformed into outputs. Despite many authors having posited the intuitive idea that technology differs across countries, in previous empirical studies this cross-country heterogeneity has generally only been allowed to exhibit itself through variations in the TFP term [Hall and Jones, 1999, Harrigan, 1999]. The fact that β is the same across countries in Equation 1.1 implies that capital and labour are combined together in the same manner; that is, the output elasticity of each input is

identical across countries. Our more generalised view allows technology, given by the coefficients β and the function ϕ , as well as total factor productivity α to differ across countries.²

Incorporating technological heterogeneity is important if we are to accurately compare cross-country productivity. Heterogeneity is implemented through the estimation of the parameters of Equation 1.2, rather than by imposition of parameters. This is a point of difference with much of the previous macroeconomic work attempting to understand cross-country variation in output per worker. Harrigan [1999] finds that the regression weight on capital is generally statistically different from the share of capital in total cost. Caselli and Feyrer [2007] note that payments to owners and sources of raw materials are likely to be more important in poorer countries. Both these findings support the view that estimation allowing for heterogeneity is preferable to a growth accounting approach imposing common parameters.

Caselli's [2005] sensitivity checks on Equation 1.1, allowing β to vary by country, find that the proportion of cross-country variation in output per worker explained is very sensitive to this choice. He also notes that there is very little empirical evidence as to whether, and how, this parameter differs between countries. Many authors talk of technology differing by country, but almost universally define the technology frontier in terms of TFP (A in Equation 1.1) and impose common β s across countries [Hall and Jones, 1999, Jerzmanowski, 2007]. The common technology assumption is challenged by the 'appropriate technology' literature, which argues that

²The 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].

different technologies are appropriate to different factor endowments. Intuitively, inputs will have less explanatory power if we restrict all countries to the same technology rather than allowing them to choose an ‘appropriate’ one from a menu. The appropriate technology view holds that the R&D leaders develop productivity-enhancing technologies that are suitable for their own K:L ratios. These then cannot be used effectively by poorer countries, which have different K:L ratios, and so the latter do not develop. Empirical evidence lending some support to this hypothesis can be found in, among others, Clark [2007] and Jerzmanowski [2007]. How, then, does our characterisation of technology in Equation 1.2 relate to that used in the appropriate technology literature?

Most appropriate technology models assume that technologies are generated for specific K:L ratios and are represented quantitatively by defining a function linking K:L to TFP [Basu and Weil, 1998]. Hence we need to be clear as to how we wish to define a difference in technology: as differences in factor ratios due to factor price heterogeneity with common coefficients, or as differences in coefficients.³ Optimal factor ratios, using the first order conditions from maximising Equation 1.2 subject to a budget constraint, can be explicitly derived from the production function and will be a function of prices and the technological coefficient(s) β . In a constant returns to scale (CRS) Cobb-Douglas production function, where p_R is the price of input R , first-order conditions give:

$$\frac{K}{L} = \frac{p_L \beta_K}{p_K \beta_L}, \quad (1.3)$$

³In this latter case, it is even technically possible, with specific sets of factor prices, to observe identical factor ratios in two countries with different technology.

and analogously for all other input pairs if they are included. In the 2-factor case with fixed prices, defining technology by the K:L ratio is equivalent to defining it by the coefficients β . If one wishes to allow prices to change or allow for more than two factors, then the usual appropriate technology definition becomes problematic.

The definition of technology is thus taken to be the coefficients of the production function. Even if one were to believe that K:L was fixed at the national level, this is less realistic 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 β s allows us to decouple TFP from technology and allow the same technology to be implemented with different levels of TFP across countries.

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 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. Thus the degree of vertical integration is one dimension of technology that is captured by the gross output framework with parameters varying by country.

One of the few empirical studies allowing for this heterogeneity is Jorgenson et al. [1987], who compare sectoral productivity across the US and Japan, allow for the input coefficients to vary across countries, and also use a gross output production function. However, their methodological approach differs in that they calculate an index of productivity rather than estimating productivity or, indeed, the other parameters of the production function. Another sectoral study with heterogeneity is that of Harrigan [1999], who uses sectoral data to compare TFP across a group of OECD countries and allows for the β s to differ by sector but not country. He finds that the data supports a model of constant returns to scale with country specific technological differences, but this conclusion has never been pursued at the microeconomic level. 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 approach is to estimate a value added production function, and they 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 indirect and raw material inputs as an integral component of production technology.

The fourth possibility in explaining why inputs appear to account for so little of the cross-country variation in output per worker is to allow for alternative functional forms. A production function such as Equation 1.2 should properly be viewed as an approximation to the true production process, and the quantitative treatment of technology may be improved by allowing for variations in the functional form which may more accurately capture the underlying process. Two generalisations of the Cobb-Douglas are the translog, which will be considered in Chapter 3, and the constant elasticity of substitution (CES), which will be considered in Chapter 4.

The fifth, and final, dimension that is investigated is the manner in which human capital is modelled. Equation 1.2, in common with much of the literature estimating Equation 1.1, specifies the effect of human capital to be equivalent to an exponential adjustment to TFP. This is extended in a number of ways. In Chapters 2 and 3, the function ϕ , describing how human capital impacts upon output, is considered as one element of technological heterogeneity and allowed to differ by country. In Chapter 3, schooling can do more than just act as a shifter of TFP. It is incorporated through adjusting labour input and, using the translog production function, allowed to be

differentially substitutable over different inputs and scales of production. In Chapter 4, the separate measures of occupation and education available in the matched firm-worker data is used to decompose human capital into four elements: skilled and unskilled workers, and their respective years of schooling. These are differentiated in a CES production function which relaxes the assumption of perfect substitutability between each of the four components. Comparing estimates of earnings and production functions using the matched data set, it is also possible to allow for education to have a wider range of impacts. In particular, Chapter 4 considers education as a sorting device and as a creator of productive skills.

The structure embodied in Equation 1.2 is used to model cross-country technology, intermediate inputs and productivity in the empirical investigation in Chapters 2, 3 and 4. Chapter 2, using a gross output framework, tests empirically for the existence of different technologies and for the sources of productivity differentials between Ghana and South Korea. Chapter 3 applies this framework to an intra-African context, and investigates if, and how, firms differ across the continent. The inter- and intra-continental results highlight a potential mechanism through which improved institutions and investment climate can lead to higher living standards: through facilitating technology choice. Given that these first chapters will establish that skills, and the manner in which they are used, are a key component of cross-country differentials, Chapter 4 uses a matched firm-worker data set to identify more precisely how human capital influences firm productivity and worker earnings in Ghana and South Korea.

Chapter 2

Sources of Productivity Difference

The labour productivity differentials across firms in Ghana and South Korea exceed those implied by macro analysis. Median value added per employee is nearly forty times higher in South Korean manufacturing firms. In this Chapter comparable firm level production functions are estimated for both countries to identify the quantitative sources of these differentials. In contrast to the conclusions of much of the macro literature, there is no significant difference in total factor productivity. Rather, the gap can be explained by the way in which firms use inputs, particularly raw materials, and the return to schooling. The share of materials in the Ghanaian production function is around twice as high, and the return to schooling, at 1.4%, is around ten times lower.

2.1 Introduction

Over the past few decades, growth rates of Asian and African economies have diverged markedly, with important consequences for development and living standards. Prior to 1964, GDP per capita was higher in Ghana than in South Korea, whereas in 2000 the situation had reversed to the extent that South Korea's GDP per capita was more than ten times that of Ghana [Heston et al., 2002]. This dramatic divergence can be seen in Figure 2.1.

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

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

$$V_{it} = A_{it} K_{it}^{\beta} H_{it}^{1-\beta} e^{u_{it}}, \quad (2.1)$$

where V_{it} is a value added measure of output, K_{it} is a measure of physical capital, A_{it} is a labour augmenting measure of total factor productivity, H_{it}

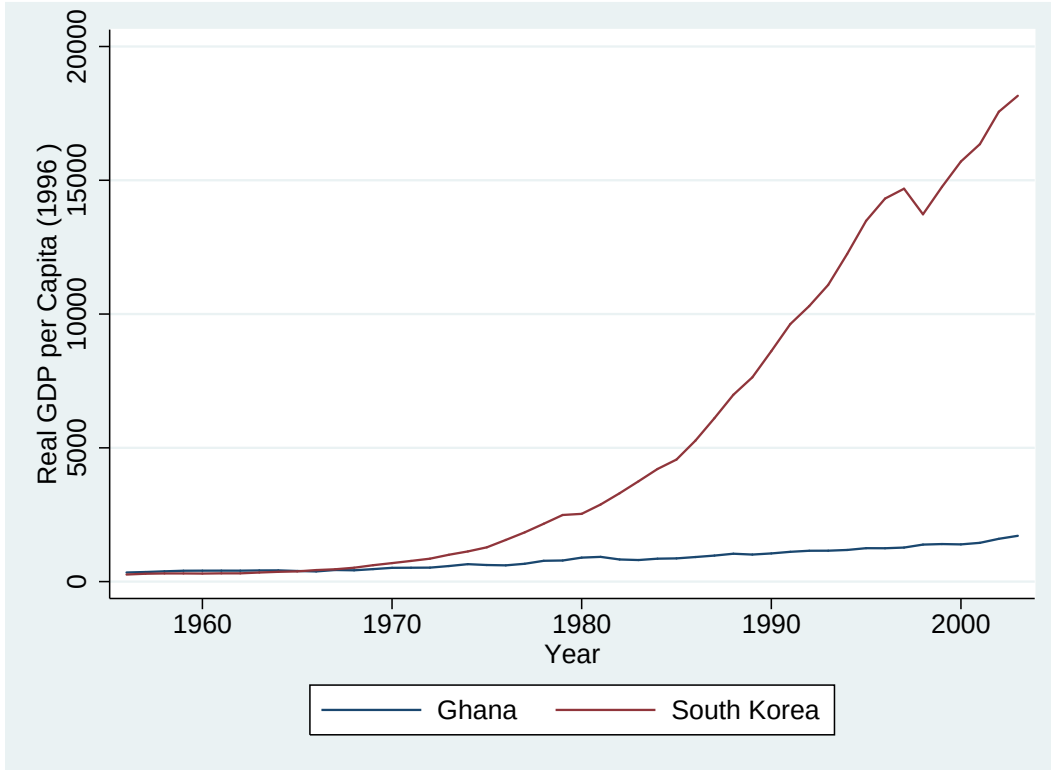


Figure 2.1: GDP per capita in Ghana and South Korea in 1996\$PPP [Heston et al., 2002].

is the amount of human capital augmented labour used in production, and u_{it} is the error term. The subscripts i and t refer to countries and time periods respectively.

The potential importance of human capital in the growth process is a focus of much of the endogenous growth literature [Acemoglu, 1996, Aghion and Howitt, 1998, Lucas, 2002]. In the model of Equation 2.1, H_{it} captures all the dimensions of labour quality which are widely regarded as a key source of differences in productivity. Clark [2007], for example, argues that the root cause of productivity differences between rich and poor countries is the latter's inability to effectively employ labour in production. The problem with

translating these growth models into an empirical form for testing, and in generalising from micro studies, is that human capital needs to be measured in a manner that makes it comparable across countries. Our innovation in this paper is to use a sufficiently general functional form that allows both average and marginal returns to human capital to differ within firms.

By extending the basic Solow model to include human capital Equation 2.1 ensures that the A_{it} term, which is total factor productivity (TFP), includes all factors other than measurable human and physical capital. An extensive literature at the macro level has argued that if we are to understand differences in incomes across countries the key is to understand what drives this measure of TFP. Hall and Jones [1999] argue for social capital, Lucas [2002] for externalities from human capital and other authors for a very large number of factors. Durlauf et al. [2005] list no fewer than 145 variables which have been included in reduced form macro growth models.

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

Such comparisons are clearly difficult. How outputs and inputs are to be

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

In the next section we set out how, within the context of a standard Cobb-Douglas production function, we can answer that question by identifying the factors that may explain these differences: is it technology, factor intensity, TFP, skills or returns to scale? The data is set out in Section 2.3 where we will show that labour productivity differentials at the micro level exceed those at the macro. The econometric approach and presentation of results is in Section 2.4. While a focus on manufacturing is clearly a narrow focus relative to work at the macro level we narrow the base of the comparison still further in Section 2.5 and look at production functions for one sector: textiles and garments. We also present robustness checks as to how successfully we have allowed for the endogeneity problems that are posed in identifying the parameters of the production function. In Section 2.6 we answer the question: why do firms in South Korea produce so much more output per worker than

Ghanaian ones? A final section concludes.

2.2 Scale, Skills and Technology

Output per worker is often used as a measure of productivity, but it is easy to construct a scenario where this is misleading. Imagine two countries of the same size using a common gross output 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 will not be an accurate measure of productivity (although may be useful in accurately reflecting relative labour incomes). This same argument can apply 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.

Production functions such as Equation 2.1 impose constant returns to scale. This restriction is not necessary and is one that we test for in our data. As will be shown below the scale on which Ghanaian and South Korean firms operate is very different. If constant returns to scale do hold in the context of a common homothetic technology then the implication is that Ghanaian firms can “scale-up” and, apart from the scale of operation, nothing will change as regards productivity or factor proportions. One reason why it might be argued such a scaling-up is not feasible, even in such a context, is that skills

interact with technology in a way not captured by the specification chosen in Equation 2.1. In particular Caselli and Coleman [2006] have pointed out that the specification imposes the assumption that workers with different educational achievements are perfect substitutes. They argue that this is clearly rejected by the macro data.

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

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

As in Hall and Jones [1999], we link human capital to years of education by the following functional form:

$$H_{it} = e^{\phi(E_{it})} L_{it}; \quad (2.2)$$

where L_{it} is the number of workers in the labour force and E_{it} is their average number of years of education. In empirical work the function can be written in a form non-linear in the variables as:

$$\phi(E_{it}) = \delta_0 + \delta_1 E_{it} + \delta_2 E_{it}^2 + v_{it}. \quad (2.3)$$

The implied value added production function is:

$$\ln V_{it} = \ln A_{it} + \beta \ln K_{it} + (1 - \beta) \phi(E_{it}) + (1 - \beta) \ln L_{it} + u_{it}. \quad (2.4)$$

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

$$\ln \frac{V_{it}}{L_{it}} = \ln A_{it} + \beta \ln \frac{K_{it}}{L_{it}} + (1 - \beta) \phi(E_{it}) + u_{it}. \quad (2.5)$$

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

return to education is the same across countries. These assumptions ensure that as human capital expands the return falls, so the net effect on underlying productivity of any increase in supply is mitigated. Studies, such as Hall and Jones [1999], that impose a common function $\phi(E_{it})$ do not allow for the empirical investigation of these issues. In the next section we estimate the return to education in the firm and do not restrict this to be concave or common between countries. There is now growing evidence that concavity does not describe the return to human capital in poor countries, particularly those in Africa. In fact there is little evidence of any return to human capital for those at the level of education below secondary which is the level for the bulk of the labour force. If this is correct then it opens up the possibility that the return on human capital may be far higher in South Korea than Ghana. This idea of heterogeneity in the cross-country return to education in the production function has also been identified as important by Krueger and Lindahl [2001], who use cross-country growth data to show that the hypothesis of a common-parameter effect of education across countries is easily rejected. The question posed in this chapter is whether the data can support a sufficiently large differential to shift up the production function by the scale required to explain differences in productivity across the two countries.

In estimating such production functions issues of functional form are crucial. Two of those issues, which have featured prominently in the literature, have been the use of gross output or value added specifications and the use of the Cobb-Douglas as a special case of more general functional forms. Research by Basu and Fernald [1995] shows that adopting a value added pro-

duction function can yield misleading results if there is imperfect competition or increasing returns to scale. We therefore propose to adopt a gross output specification and test whether important information is lost when a value added specification is used.² We extend the specification in Equation 2.1 by the inclusion of raw material inputs (M_{it}) and indirect costs (I_{it}) and we are now explicit as to the potential importance of time invariant unobservables in the fixed effects (μ_i) and time varying common unobservables (θ_t). Letting $\beta_L^* = 1 - \beta_K - \beta_I - \beta_M$ we have:

$$Y_{it} = AK_{it}^{\beta_K} M_{it}^{\beta_M} I_{it}^{\beta_I} H_{it}^{\beta_L^*} e^{\mu_i} e^{\theta_t} e^{u_{it}}. \quad (2.6)$$

Note that the subscripts on the TFP term have been dropped as these are now incorporated through μ and θ . We obtain an equation that includes observable human capital by similar assumptions to those already made:

$$\ln Y_{it} = A + \theta_t + \beta_K \ln K_{it} + \beta_L^* \ln L_{it} + \beta_I \ln I_{it} + \beta_M \ln M_{it} + \beta_L^* \phi(E_{it}) + \mu_i + u_{it}. \quad (2.7)$$

From this we obtain the basic specification for this paper:

$$\ln Y_{it} = A + \theta_t + \beta_K \ln K_{it} + \beta_L^* \ln L_{it} + \beta_I \ln I_{it} + \beta_M \ln M_{it} + \beta_L^* (\delta_1 E_{it} + \delta_2 E_{it}^2) + \mu_i + u_{it}. \quad (2.8)$$

In this gross output production function we need measures for five inputs: physical capital, K , raw material inputs, M , indirect inputs, I , years of education, E , and labour, L . The empirical challenge is to measure these

²Any biases from imperfect competition are also reduced through the use of firm specific input and output price deflators.

variables in a way that ensures cross-country comparability while also allowing us to address the issues of endogeneity and the role of unobservables which have dominated attempts to estimate this relationship empirically (as reviewed in Tybout [2000]).

Using Equation 2.8 we can identify differences in returns to scale, skills and technology. Returns to scale are given by the sum of the exponents and we can test for the constant returns hypothesis ($\beta_L = 1 - \beta_K - \beta_I - \beta_M$) where β_L is the unrestricted coefficient on labour. Differences in skills are captured, in part, by allowing for variation in the measure of human capital which is the years of education (E) and, in part, by seeking to identify the return on human capital across the firms which is a function of (δ_1, δ_2) .

In this chapter technology refers to the way in which firms combine inputs to produce output; sometimes referred to as the ‘blueprints’ of production. If the ‘blueprints’ used by firms across these countries differ then the parameters $(\theta, \beta_K, \beta_I, \beta_M, \delta_1, \delta_2)$ will also differ. As we are allowing the parameters on education to vary across the countries this aspect of technology acts to shift up the production function. In fact, in this specification, human capital acts just like any other factor which is assumed to affect the underlying TFP of the firm.

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

$$V_{it} = Y_{it} - IM_{it} \text{ and } dV_{it} = dY_{it} - dIM_{it}. \quad (2.9)$$

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

$$V_{it} = Y_{it} - s_{im}Y_{it} \quad (2.10)$$

$$= (1 - s_{im})Y_{it}, \text{ and} \quad (2.11)$$

$$\frac{dV_{it}}{V_{it}} = \frac{dY_{it} - dIM_{it}}{Y_{it} - IM_{it}} \quad (2.12)$$

$$= \frac{1}{(1 - s_{im})} \frac{dY_{it}}{Y_{it}} - \frac{1}{(1 - s_{im})} \frac{IM_{it}}{Y_{it}} \frac{dIM_{it}}{IM_{it}} \quad (2.13)$$

$$= \frac{1}{(1 - s_{im})} \frac{dY_{it}}{Y_{it}} - \frac{s_{im}}{(1 - s_{im})} \frac{dIM_{it}}{IM_{it}} \quad (2.14)$$

$$= \frac{1}{(1 - s_{im})} \left[\frac{dY_{it}}{Y_{it}} - s_{im} \frac{dIM_{it}}{IM_{it}} \right]. \quad (2.15)$$

If gross output and inputs are growing at the same rate then value added will also be growing at that rate. Basu and Fernald [1995, pp172] discuss the biases that can arise if the value added specification is used. Here we note that we can interpret a move from the gross output specification in Equation 2.8 to a value added one in terms of such growth rates:

$$\frac{dV_{it}}{V_{it}} = \frac{1}{(1 - s_{im})} \left[\beta_K \frac{dK_{it}}{K_{it}} - (1 - \beta_K - \beta_I - \beta_M) \frac{dL_{it}}{L_{it}} - \beta_L^* (\delta_1 dE_{it} + \delta_2 dE_{it}^2) \right]. \quad (2.16)$$

This bias on the input coefficients also holds in a levels context. Let a , b_K and b_L refer to the value added estimates of TFP and the coefficients on capital and labour respectively. Simplifying to a three factor gross output model, let A , β_K , β_L and β_M refer to the gross output estimates of TFP and the coefficients on capital, labour and raw materials. Assuming constant

returns to scale, the bias in the value added coefficients will be as follows:

$$\ln a = \ln A + \frac{\beta_M}{1 - \beta_M} \ln \gamma + \ln(1 - \frac{\gamma}{A}), b_K = \frac{\beta_K}{\beta_K + \beta_L}, b_L = \frac{\beta_L}{\beta_K + \beta_L}. \quad (2.17)$$

The proof of this equation, and the definition of the constant γ , is given in Appendix 2.B. The relativity of b_K and b_L in a value added equation is driven by the relativity of the corresponding gross output parameters. The estimate of TFP in a value added specification will be a biased estimate of the true gross output TFP and this bias will generally be increasing in β_M . We will use this specification in a comparison of the results from our micro analysis with the work using macro GDP data.

As well as the difference in the use of value added and gross output production functions, our work will differ from the macroeconomic literature based upon Equation 2.1 due to issues of aggregation. Firstly, the macroeconomic parameters will be capturing some additional effects such as spillovers between industries.³ More importantly, though, there is limited evidence as to the quantitative relationship between micro and aggregated production function estimates, and much of what evidence does exist is theoretical [Jones, 2005].⁴ Our work differs from the macro approach in that it allows us to estimate technological differences across micro units. While our approach cannot perfectly inform the macro issue as to the country level differences in productivity that obtain, it can address that question for a sector, manufacturing, which has been important for the development of many

³Although the importance of these is questioned by Basu and Fernald [1995].

⁴Using an index number approach, aggregate TFP is the weighted average of the TFP of its constituent units (e.g. firms) but this is an accounting identity and will not necessarily carry over into production function estimates.

economies. Whether the factors we identify as important at the micro manufacturing firm level pertain to the overall structure of the economy clearly require more extensive sectoral data than we have.

2.3 Productivity in Ghanaian and South Korean Firms

The data used for the cross-country comparison are unbalanced panels of 863 South Korean manufacturing firms observed for 3 years and 312 Ghanaian manufacturing firms observed for up to 12 years. Both data sets were collected in a similar manner by interviews with firm management. The Ghanaian data cover the period 1991-2002 and the South Korean data cover the period 1996-98. Söderbom and Teal [2004] use the Ghana data over the period from 1991 to 1997 and the present study extends the data set but retains the definitions used in that paper. The South Korean data are described in Hallward-Driemeier et al. [2001]. The period 1996-1998 is common to both data sets, with the Ghanaian data also including some additional years. There is a literature investigating cyclical effects of TFP, with TFP generally considered pro-cyclical; however, we do not investigate cyclical effects here and account for them through the inclusion of year dummies. The estimates of TFP that will be presented are implicitly for the omitted year (which is 1991 in Ghana and 1998 in South Korea).

The macroeconomic literature based upon Equation 2.1 uses aggregate data to compare TFP across economies; whereas, we have outlined an ap-

proach where data on a panel of manufacturing firms will be used. While our focus is on the microeconomic determinants of productivity, one could ask how informative this will be as to aggregate differences? In 2000, the share of manufacturing in total value added was 9.03% in Ghana and 26.14% in South Korea. Over the period 1995-2000, the growth rate in manufacturing value added exceeded the growth rate in non-manufacturing GDP in both countries: 5.17% versus 4.28% in Ghana and 6.83% versus 2.44% in South Korea [UNIDO, 2008]. While manufacturing is clearly an important part of both economies, it is of course not possible to claim that manufacturing TFP, or that of our sub-sample, will exactly reflect aggregate TFP; however, the comparison is still relevant. Where interest lies in productivity rather than in income, international comparisons of TFP are difficult when the sectoral composition of countries differs substantially. The question of whether Ghanaian manufacturing is as productive as South Korean manufacturing is a different one to the question of whether the Ghanaian economy has a greater share of low productivity activities. If Ghana's lower aggregate TFP is the result of sectoral composition only then it is not accurate to talk of Ghana as being 'less productive' if TFP is not lower in comparable sectors.

The key data problem we face is making outputs and inputs comparable both across firms within a country and across countries. We do this in three stages. Firstly, the variables are constructed so that the definitions are consistent across countries. Secondly, we deflate the values of outputs and inputs by firm specific domestic prices so as to render them comparable within the country. Finally, they are converted to international prices by means of the purchasing power parity (PPP) price indices available from the PENN

World Table [Heston et al., 2002]. The result is a series of comparable values which should enable us to compare productivity across the manufacturing sectors of South Korea and Ghana.⁵

For both Ghana and South Korea we have firm level price deflators for output and some of the inputs. We have used the primary data from the surveys to obtain measures of the following: output; inputs classified as raw material inputs; and “other inputs”, which are primarily indirect costs (electricity, other energy and rent). We have firm level deflators for both output and raw material inputs but not for indirect costs. We proceeded by deflating output and raw material prices by these firm level deflators and then converting these values to PPP\$ by using the PPP deflator for the base year.⁶ For indirect costs, where no appropriate firm level deflator was available, we have used the PPP consumption deflator for each year. These deflators render the data comparable over time within the country and, as they are generally firm based, ensure that the variables measure changes in real quantities (at least for output and raw materials) and not higher revenues or lower costs associated with market power.

The variation in firm level prices for output and inputs is important for the identification of Equation 2.8. Bond and Söderbom [2005] show that if all inputs are costlessly adjustable and chosen optimally then, if prices are common between firms, a Cobb-Douglas production function will be unidentified. Taking the first derivative of a Cobb-Douglas production function

⁵Details of the calculations are given in Appendix 2.A. In the text we focus on the key decisions made to render the data comparable across the two countries.

⁶In cases where these firm level price indices were not reported they were assumed to be equal to the average of firms in the same manufacturing sub-sector.

leads to a first-order condition where quantities are functions of prices and the (firm specific) TFP term and so, with common prices, inputs are all collinear with the TFP term and so are unidentified. This problem is mitigated in the presence of adjustment costs or where firms face different factor prices. That input prices and/or adjustment costs vary between firms is a plausible assumption in this application. The input prices faced by firms can still differ even if one were to believe that input markets are perfect. For example: the price of labour will differ with commuting distances; the price of capital will differ with proximity and expertise of repair and maintenance firms, or with credit constraints. These are examples of variation that may be more pronounced in Ghana. Contracts for the supply of raw materials will contain prices which will vary depending on when the contract was signed and the relative use of spot or forward markets. This kind of variation may be more pronounced in South Korea. Transport costs for physical intermediate inputs will also be firm specific. The persistence of inputs over time is indicative that they are not perfectly adjustable. As long as the adjustment costs between inputs are not too closely correlated and differ by firm this will achieve identification even if prices were identical.

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

the investment series and assume a depreciation rate rather than using the reported values of the capital stock.

Having made the data comparable within the country we then proceed to render it comparable across countries by means of country level PPP deflators for the base year which is 1991 for Ghana and 1996 for South Korea. We use the GDP PPP deflator for output, the investment PPP deflator for capital and the consumption PPP deflator for materials, the latter being the same as that already used for the indirect costs. It is at this stage that problems of comparability are most pronounced. Given our interest in comparing TFP, not only across firms within a country but also across firms in such very different countries as Ghana and South Korea, any error in this deflation will appear in the TFP difference. Our defense is that the PPP exchange rates represent our best estimate of price level differences across countries. Note that our procedure means that exchange rate fluctuations over time will not impact upon the estimates of the production function coefficients, as domestic deflators were used to convert into real domestic currency values prior to the international conversion. Any error in the PPP exchange rate between 1991 Ghanaian Cedis and 1996 South Korean Won will appear as part of the TFP term.

Finally we turn to how the human capital variables have been created. The measure of labour input is weekly hours worked. For Ghana we use the firm level data on employment and average hours worked. In South Korea we do not have firm level data on hours worked, and so we use the sub-sector (ISIC 2-digit) averages from the International Labour Organisation. The only common measure of quality available was the average number of years

of education of workers in the firm. For Ghana we have time variation in this measure, which was obtained from labour market surveys carried out at the same time as the firm surveys. These surveys contain information on the years of education by occupation of the worker and we have aggregated up the individual level data to a firm basis using the occupational structure of the firm. The proportion of the workforce that has completed various levels of education is used for South Korea and, from this, we impute an implied average by assuming that workers finish the level of reported education. This measure has no time variation. In order to make the measures comparable we remove the time variation in the Ghanaian data by taking an average for each firm. Years of education will not perfectly capture skills of workers, although there is evidence that it is a useful proxy [Boissiere et al., 1985, Jones, 2001, Biesebroeck, 2007]. The interplay between skills, education and human capital is explored in more detail in Chapter 4.

Table 2.1 presents the results of these calculations. The median output per employee is twenty times higher in South Korean than in Ghanaian firms, whilst the differential in terms of median value added per employee is nearly forty times. The differences in capital per worker are larger still: with the medians differing by a factor of nearly fifty times. Clearly the firms are performing very differently and using quite different factor intensities. To what extent can our production function capture these differences?

Variable	Ghana		South Korea	
	Mean	Median	Mean	Median
Output (Y)	2,753 (10,003)	179	40,992 (74,530)	16,210
Capital (K)	1,180 (5,729)	21	21,771 (66,583)	4,798
Employment (L)	73 (155)	22	122 (125)	84
Indirect inputs (I)	651 (2,677)	15	648 (1,890)	216
Materials (M)	1,183 (4,969)	82	14,005 (27,630)	4,719
Weekly man-hours (H)	3,297 (7,410)	997	5,659 (5,861)	3,842
Y/L	20.3 (35.3)	9.8	290.5 (355.4)	192.8
K/L	7.77 (29.4)	1.32	115 (207)	61
I/L	3.21 (7.31)	0.85	4.50 (8.41)	2.32
M/L	10.0 (20.0)	4.1	98 (132)	60
V/L	7.1 (16.7)	3.1	188 (303)	116
Hours	46 (9)	45	46 (2)	46
Education(yrs)	10.0 (2.5)	10.1	12.7 (1.2)	12.7
Firms	257		358	
Observations	1884		919	

Table 2.1: 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.

2.4 Estimating Technology and the Return to Skills

A common approach to the issue of assessing differences across firms is to model the production frontier, defined as best practice technique, and to assess other firms relative to this frontier. This approach, where panel data is available, essentially denotes the most efficient firm as the one with the highest level of TFP as identified from the time-invariant fixed effect from the estimated production function. Frontier methods are not pursued as they have the drawback that maximum efficiency could be attributed to the firm with the largest measurement error in the relevant direction, a severe limitation where measurement error may be significant. Frontier methods also impose a common technology and error structure; thereby, limiting the scope of firms that can be compared. Furthermore, identification via assumption on the distribution of inefficiency is problematic because the assumption is not testable.

Rather than follow the frontier approach we will proceed by seeking a separate estimate of Equation 2.8 for both Ghana and South Korea. As we have sought to make the units of measurement comparable across the countries we can then determine the extent of any difference in TFP. The estimation of such production functions involves a number of econometric problems which, despite having been the subject of a considerable literature, are still under active discussion. Endogeneity resulting from unobserved time-varying factors being correlated with inputs, encompassing both omitted variable bias and measurement error, has generally been seen as the critical issue for the

estimation of production functions. There have been four main techniques in the literature to overcome endogeneity problems: instrumental variable estimation (IV); fixed effects estimators (FE); structural identification; and generalised method of moments (GMM) panel data estimators. The difficulty in finding suitable instrumental variables, the bias in FE estimators from measurement error and multicollinearity problems with structural identification [Akerberg et al., 2005] lead to the GMM approach being the primary one adopted in this thesis, although we also present results for some of the other methods.⁷

The system GMM approach, which is discussed in more detail in Appendix 2.C, uses the autocorrelation structure of the residuals to obtain a set of moment conditions. In the language of instrumental variable estimation, lags of levels are used as instruments for first-differences and lags of first-differences are used as instruments for levels.⁸ The particular set of moment conditions that is available is dependent upon the autocorrelation structure of the residuals. The GMM estimator and the diagnostic tests are implemented using the `xtabond2` command [Roodman, 2006] in the STATA statistical package. The autocorrelation structure is determined through the use of the Arellano-Bond [1991] *m* statistics. These test the null of no autocorrelation of the specified order and determine how many lags need to be

⁷The adjustment to the structural identification approach outlined by Akerberg et al [2005] was not pursued as we believe that unobservables may impact current choices of intermediate inputs and because it cannot allow for fixed effects in small-T panels such as ours.

⁸A difference GMM estimator, using only lags as levels as instruments for first differences, is also available. For highly persistent series this will be biased downwards in the direction of the FE estimator. Difference GMM estimates were found to be biased as expected and so are not presented.

taken in order to arrive at valid moment conditions.

The overall validity of the moment conditions (or, equivalently, of the instruments) is validated through the use of the Sargan test with the null hypothesis that the instruments are valid (ie exogenous). The original version of this estimator consisted solely of an equation in first-differences with appropriately lagged levels as instruments. Arellano and Bond [1991] noted that this ignored other available moment conditions and was also problematic if variables were relatively time-invariant and, so, the estimator was combined with a levels equation with lags of differences as additional instruments [Blundell and Bond, 1998]. This resulting system GMM estimator nests the original difference GMM estimator and so a difference-in-Sargan test can be used to check the validity of the additional instruments used in the levels equation.

The first-differencing operation not only removes unobserved firm specific effects but also time-invariant explanatory variables. This presents a problem if the effects of time-invariant variables are of interest as the instrumenting procedure described above is only available for endogenous variables that are time-varying. In our equations, this means that we are able to use the moment conditions to instrument capital, labour, materials and indirect costs but not education. In Table 2.2 we assume that education is exogenous. Due to concern that it may be correlated with unobservables, and to check that this assumption is not material to our conclusions, we undertake some more detailed analysis of alternative instrument sets in Section 2.5.

The basic result in this chapter, presented in Table 2.2, compares the Ghanaian and South Korean firms using identical specifications and imposes,

after testing, constant returns to scale. Consider first the OLS results. We would expect these to be biased by the presence of unobservables, such as management ability and measurement error. The coefficients on variables that are positively correlated with unobservables will be biased upwards while those that are negatively correlated will be biased downwards. We use two approaches to investigate whether the OLS coefficients are biased by endogeneity. Firstly, we implement a fixed-effects estimator. This removes firm specific time-invariant unobservables from the data, and hence also removes any bias they may cause. As is typical in production function estimation, likely due to measurement error, the coefficients in the unrestricted fixed effects estimator are implausibly low but become reasonable with constant returns imposed. As constant returns to scale are not rejected in any of the other specifications we are comfortable imposing this restriction for the fixed effects estimator. The system GMM panel data estimator allows for the autoregressive structure of productivity shocks and measurement error to be unrestricted, and, further, allows both of the former and the fixed effects to be freely correlated with input choices. Thus, from an endogeneity perspective, the GMM results should be unbiased if the instruments are valid and if education is exogenous. We test for autocorrelation of varying degree and lag the instruments sufficiently given the results of these tests. The subsequent Sargan test does not reject the validity of the instruments even when we implement the correction proposed by Bowsher [2002] to correct for the known tendency of this test to under-reject.⁹

⁹The Difference-in-Sargan test, which tests for the validity of the additional lagged differences as instruments in the levels equation, while not reported, also does not reject the instruments.

	Ghana	Ghana	Ghana	Korea	Korea	Korea
	OLS	FE	GMM	OLS	FE	GMM
	1	2	3	4	5	6
lnK	0.0349** (0.0116)	0.0261* (0.0104)	0.0471* (0.0214)	0.1095*** (0.0278)	0.0835*** (0.0246)	0.1620 (0.0842)
lnH	0.1292*** (0.0144)	0.1830*** (0.0134)	0.1387*** (0.0346)	0.4135*** (0.0365)	0.4651*** (0.0374)	0.3469*** (0.0915)
lnI	0.1844*** (0.0177)	0.1498*** (0.0095)	0.1561*** (0.0300)	0.2247*** (0.0302)	0.1999*** (0.0254)	0.1484* (0.0605)
lnM	0.6514*** (0.0235)	0.6412*** (0.0095)	0.6582*** (0.0405)	0.2523*** (0.0369)	0.2514*** (0.0251)	0.3426*** (0.0773)
E	-0.0939* (0.0386)		-0.1099* (0.0537)	0.4747 (0.2525)		0.4437 (0.2415)
E ²	0.0062** (0.0022)		0.0071* (0.0032)	-0.0141 (0.0103)		-0.0135 (0.0098)
Cons	2.1160*** (0.2167)	1.9445*** (0.0561)	2.1581*** (0.3488)	1.3509 (1.5745)	5.3932*** (0.2425)	0.9462 (1.5576)
AR1	0.0000		0.0000	0.0000		0.4819
AR2	0.0000		0.0000	0.0000		
AR3	0.0000		0.4593			
Sargan			126.1			15.34
Sargan df			129			17
Sargan p			0.5554			0.5708
Obs	1880	1884	1880	918	919	918
Firms		257	254		358	357
CRS	0.0793	0.0001	0.7500	0.3159	0.0000	0.1707
Educ	0.0091		0.0608	0.0000		0.0000

Table 2.2: The dependent variable is log of real output in 1996 \$PPP. Education is included as a quadratic effect in Columns 1, 3, 4 and 6. 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. Educ is a Wald test of the null hypothesis that both education coefficients are zero. The autocorrelation test for the system GMM estimates cannot reject AR2 in first differences for Ghana so we take the ‘t-3’ and ‘t-4’ lags as instruments using the restriction suggested by Bowsher [2001]. AR1 was not rejected for South Korea so all possible lags were used. Year dummies were included but have not been reported. Standard errors are robust to heteroskedasticity and autocorrelation, and those for the OLS and FE regressions have been calculated using a clustering method that allows for the errors to be correlated within firms. The symbols */**/** identify estimates significantly different from zero at p=0.05/0.01/0.001 respectively.

	Ghana	Ghana	Korea	Korea
	OLS	GMM	OLS	GMM
	1	2	3	4
lnK	0.0387** (0.0117)	0.0586** (0.0207)	0.1106*** (0.0276)	0.1652* (0.0842)
lnH	0.1168*** (0.0130)	0.1372*** (0.0331)	0.4140*** (0.0366)	0.3462*** (0.0911)
lnE	0.1017 (0.0686)	0.0956 (0.0879)	1.5103*** (0.2839)	1.2906*** (0.2943)
lnI	0.1895*** (0.0180)	0.1577*** (0.0301)	0.2239*** (0.0303)	0.1489* (0.0606)
lnM	0.6550*** (0.0233)	0.6465*** (0.0418)	0.2515*** (0.0369)	0.3397*** (0.0768)
Cons	1.5466*** (0.1781)	1.5928*** (0.2525)	1.2583 (0.6420)	1.0978 (0.7016)
AR1	0.0000	0.0000	0.0000	0.4881
AR2	0.0000	0.0000	0.0000	
AR3	0.0000	0.4710		
Sargan		125.5		15.36
Sargan df		129		17
Sargan p		0.5695		0.5695
Obs	1880	1880	918	918
Firms		254		357
CRS	0.0491	0.5223	0.0347	0.1558

Table 2.3: The dependent variable is log of real output in 1996 \$PPP. Education is included as a logarithmic term. Other notes as for Table 2.2.

	Ghana	Ghana	Korea	Korea
	OLS	GMM	OLS	GMM
	1	2	3	4
lnK	0.0428*** (0.0109)	0.0622** (0.0200)	0.1243*** (0.0285)	0.1827* (0.0841)
lnH	0.1143*** (0.0131)	0.1347*** (0.0331)	0.3810*** (0.0340)	0.3223*** (0.0909)
lnI	0.1909*** (0.0181)	0.1599*** (0.0301)	0.2259*** (0.0305)	0.1416* (0.0634)
lnM	0.6520*** (0.0228)	0.6433*** (0.0435)	0.2688*** (0.0355)	0.3535*** (0.0796)
Cons	1.7756*** (0.0869)	1.8098*** (0.1612)	4.8601*** (0.2337)	4.1783*** (0.6506)
AR1	0.0000	0.0000	0.0000	0.5061
AR2	0.0000	0.0000	0.0000	
AR3	0.0000	0.4727		
Sargan		127.1		14.30
Sargan df		129		17
Sargan p		0.5296		0.6460
Obs	1884	1884	919	919
Firms		257		358
CRS	0.0326	0.4311	0.1028	0.1787

Table 2.4: The dependent variable is log of real output in 1996 \$PPP. Other notes as for Table 2.2.

	Ghana	Ghana	Korea	Korea
	GMM	GMM	GMM	GMM
	1	2	3	4
lnK	0.3346*** (0.0950)	0.3790*** (0.0787)	0.1938 (0.1396)	0.2208 (0.1383)
lnH	0.6654*** (0.0950)	0.6210*** (0.0787)	0.8062*** (0.1396)	0.7792*** (0.1383)
E	-0.5535*** (0.1508)		0.5384 (0.3796)	
E ²	0.0305** (0.0101)		-0.0147 (0.0153)	
Cons	-1.5687* (0.6879)	-4.0674*** (0.2876)	-4.5966* (2.3307)	-0.3495 (1.0097)
AR1	0.0000	0.0000	0.1200	0.1233
AR2	0.0005	0.0004		
AR3	0.8118	0.8497		
Sargan	75.94	75.58	5.798	3.854
Sargan df	65	65	9	9
Sargan p	0.1666	0.1736	0.7599	0.9207
Obs	1774	1778	907	908
Firms	253	256	354	355
CRS	0.0583	0.0402	0.1424	0.1855
Educ	0.0002		0.0000	

Table 2.5: The dependent variable is log real value added in 1996 \$PPP. Other notes as for Table 2.2.

	E_t	GMM-IV	GMM-IV	Textiles and Garments	
	Ghana	Ghana	Korea	Ghana	Korea
	1	2	3	4	5
lnK	0.0537* (0.0215)	0.0383 (0.0216)	0.1904* (0.0950)	0.0566* (0.0237)	0.0597 (0.0836)
lnH	0.1111*** (0.0318)	0.1287*** (0.0323)	0.2964* (0.1219)	0.0737* (0.0297)	0.2960 (0.2108)
lnI	0.1557*** (0.0289)	0.1957*** (0.0326)	0.1774** (0.0656)	0.0971* (0.0412)	0.3697** (0.1316)
lnM	0.6796*** (0.0421)	0.6373*** (0.0409)	0.3358*** (0.0837)	0.7727*** (0.0323)	0.2746* (0.1178)
E	0.0403 (0.0390)	0.0768* (0.0376)	0.2297 (0.1563)	0.1848 (0.5981)	1.7762* (0.8083)
E ²	-0.0018 (0.0021)			-0.0073 (0.0312)	-0.0631 (0.0334)
Cons	1.4761*** (0.2512)	1.0814** (0.3633)	1.1853 (1.5619)	0.4217 (2.8340)	-7.4349 (4.9487)
AR1	0.0000	0.0000	0.5196	0.0046	0.3518
AR2	0.0001	0.0000		0.0555	
AR3	0.4227	0.4108		0.0090	
Sargan	162.7	131.3	19.22	34.16	15.80
Sargan df	160	130	19	129	17
Sargan p	0.4260	0.4515	0.4423	1.0000	0.5379
Obs	1842	1851	876	419	190
Firms	254	252	345	54	77
CRS	0.1434	0.0155	0.2815	0.7030	0.2694
Educ	0.5430			0.4766	0.0000

Table 2.6: Robustness Checks. The dependent variable is log of real output in 1996 \$PPP. All estimators are system GMM as in Table 2.2 with additional instruments as specified. Column 1 uses the time-varying measures of education for Ghana to check that the averaging by firm done earlier for consistency is not causing bias. Columns 2 and 3 assume that education is completely endogenous and uses wages and material input prices as additional instruments. Columns 4 and 5 repeat the regressions of Table 2.2 solely for those firms in the Textiles and Garments sector. Other notes as for Table 2.2.

Ghana	OLS	OLS	GMM	GMM	GMM-IV	GMM-IV
	1	2	3	4	5	6
lnK	0.0471* (0.0192)	0.0470* (0.0192)	0.0944* (0.0414)	0.0931* (0.0398)	0.1075** (0.0363)	0.1057** (0.0356)
lnL	0.0996*** (0.0244)	0.1000*** (0.0246)	0.1092 (0.0777)	0.1011 (0.0830)	0.0590 (0.0547)	0.0575 (0.0541)
lnI	0.1780*** (0.0300)	0.1778*** (0.0298)	0.1323* (0.0517)	0.1195* (0.0511)	0.1487** (0.0467)	0.1458** (0.0469)
lnM	0.6753*** (0.0342)	0.6752*** (0.0342)	0.6641*** (0.0769)	0.6863*** (0.0836)	0.6848*** (0.0761)	0.6909*** (0.0786)
E	0.0102 (0.0244)	0.0077 (0.0099)	-0.0225 (0.0395)	-0.0004 (0.0152)	-0.0090 (0.0365)	-0.0095 (0.0151)
E ²	-0.0002 (0.0015)		0.0014 (0.0025)		-0.0000 (0.0023)	
Constant	2.4027*** (0.3489)	2.4161*** (0.3465)	2.6244** (0.9965)	2.4175* (1.0869)	1.9887* (0.8209)	1.9656* (0.7957)
Obs	564	564	564	564	564	564
Firms			143	143	143	143
CRS	0.0317	0.0317	0.8840	0.6216	0.1448	0.2397
Educ	0.7348	0.4405	0.8498	0.9795	0.8077	0.5307
AR1			0.0066	0.0086	0.0079	0.0089
AR2			0.1610	0.1559	0.1576	0.1495
Sargan			36.22	29.45	43.28	37.42
Sargan df			43	36	57	50
Sargan p			0.7584	0.7717	0.9101	0.9057

Table 2.7: Additional robustness checks with endogenous education incorporating firm level averages of worker background as additional instruments. The dependent variable is log of real output in 1996 \$PPP. The measure of labour input is unadjusted for hours worked. Columns 1-4 are repetitions of the estimates in Table 2.2 only for those observations for which the additional instruments are available. For a sample of workers from this sub-sample of the firms, we have the following data on each of the worker's parents: years of education, dummy if the parent is a farmer and a dummy if the parent is a professional. In addition, we also have variables indicating how far the workers lived from primary and secondary schools when they were six and twelve years old respectively. Firm level averages of these variables are constructed using the occupational structure. Constant returns to scale have been imposed and CRS is a p-value from the null that this restriction is valid. As AR2 is not rejected the instruments are the t-2 and t-3 lags. Substantively identical results are obtained if the time-invariant measure of education is used. Other notes as for Table 2.2.

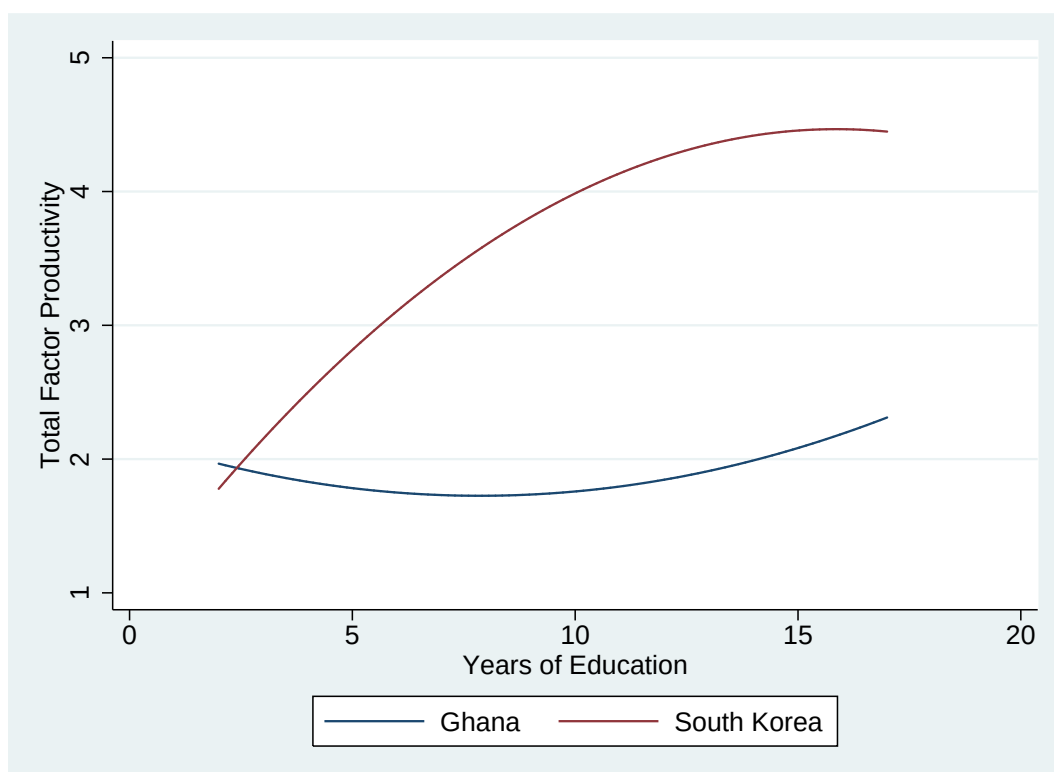


Figure 2.2: The return to education function for Ghanaian and South Korean firms.

Our main result focuses on the differing impact of education on firm output in the two countries. The quadratic functional form allows for the possibility that the shape and the magnitude of the return differs. The return implied by Table 2.2 in Ghana is small and convex while that in South Korea is larger and concave. Note that, while the South Korean coefficients are not individually significant, the joint null hypothesis that the linear and quadratic terms are equal to zero is easily rejected. Taking the first derivative of the quadratic and evaluating at the sample mean indicates an implied rate of return of 3% in Ghana and 10% in South Korea.¹⁰ The return to education functions are plotted in Figure 2.2. The average return to education in each country can also be calculated. As there are no observations at very low levels of education we are wary of extrapolating the quadratic too far. As such, the average rate of return is calculated assuming that the total return to education is reflected in the quadratic from three years to the maximum observed in each country. That is, we take $\phi(3)$ (rather than $\phi(0)$) as an estimate of the intercept of the return to education function. This calculation yields average rates of return on years of education of 15.2% in South Korea and 1.4% in Ghana.¹¹

Compared to the other specifications, the constant term in the fixed effect equation is much higher for South Korea and virtually identical for Ghana. This implies that time-invariant factors, including, in our model, education, are important for explaining productivity in South Korea but not in Ghana.

¹⁰Calculated as $-0.1099 + (2 \times 0.0071 \times 10.0) = 0.032$ for Ghana and $0.4437 - (2 \times 0.0135 \times 12.7) = 0.101$ for South Korea.

¹¹Calculated as $(\phi(15) - \phi(3))/15 = (-0.051 - -0.267)/15 = 0.014$ for Ghana and $(\phi(16) - \phi(3))/16 = (3.643 - 1.210)/16 = 0.152$ for South Korea.

In Table 2.3 we use a logarithmic function in Equation 2.3 as a way of imposing concavity in the return, while still allowing them to differ across countries. This compares to the approach in Hall and Jones [1999] where concavity was imposed with a common rate of return. Based upon the quadratic specification we expect that this functional form will be rejected for Ghana but not for South Korea, and the empirical results confirm this. The Ghanaian coefficient is not significantly different from zero, while the greater structure imposed means that the South Korean coefficient is now highly significant. The implied rate of return at the mean is 10%.¹²

As we have chosen units so that they are comparable across countries we can clearly interpret any differences in the constant term in the regressions as a difference in TFP. In Table 2.3, with concavity imposed, the constant terms are almost equal. In Table 2.4 education is not included in the production function and the logarithmic TFP difference between Ghana and South Korea is 2.4. Using the implied rates of return calculated from Table 2.2 the difference that can be attributable to education is $e^{0.10*12-0.03*10} = 2.4$. This is exactly the implied difference in TFP in Table 2.4 where we exclude education from the production function.

The estimation of value added Equation 2.5 is presented in Table 2.5 and we would anticipate that these coefficients will be biased if the gross output is the correct specification. Equation 2.17 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 2.2, the im-

¹²Calculated as 1.2906/12.7.

plied $b_K \approx \frac{1}{3}$ for both Ghana and South Korea.¹³ This is consistent with our empirical estimates of the slope coefficients of the value added production function in Table 2.5, the estimates for 3 Sub-Saharan African countries in Van Biesebroeck [2007], 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 use of a value added specification to model the production process. The estimate of the productivity term will also be biased, with the direction and size of the bias being a function of prices and technology. The logarithmic difference in TFP when education is excluded is 3.7, compared to the 2.4 in the corresponding gross output specification in Table 2.4. Even allowing for a quadratic education effect, as in Columns 1 and 3, the implied logarithmic TFP difference at $E = 10$ is 3.4.

Any difference in point estimates on the inputs can be interpreted as differences in technology across the countries. Table 2.2 shows that there is a clear difference in technology with Ghanaian firms having a substantially higher material elasticity of output and lower capital and labour elasticities. This, together with the results already presented for the value added specification, suggests that a gross output specification of the production function is to be preferred. The share of inputs comprised of intermediate inputs is much higher in Ghana than in South Korea: 81% as opposed to just under 50%. This means that, for every unit of output produced, Ghanaian firms are spending relatively more on raw materials and relatively less on payments

¹³Note that if we have CRS and a constant $\beta_K : \beta_L$ ratio, then technology could be uniquely indexed by a single parameter β_K . More specifically, in the context of Equation 1.2 with quality adjusted labour, we have $\ln \frac{Y}{M} = \ln A + \beta_K [\ln \frac{K}{M} + \rho \ln \frac{L}{M}]$ where $\rho = \frac{\beta_L}{\beta_K}$.

to workers and capital owners. If technology evolved such that the share of raw materials in production could be reduced then a greater share of income would be available for workers and capital owners and, hence, for consumption. This would also have the effect of raising the return on capital and on labour which would stimulate investment in plant and equipment and in human capital. To understand how firms in Ghana may evolve to resemble those in South Korea a consideration of input technology appears to be important.

2.5 Some Robustness Checks

Prior to interpreting the main result, we consider possible problems with the regressions reported in Table 2.2. The first is the possibility that the instrumentation procedure we have used is not valid. The second is that, while we are using a far more narrowly defined set of production activities than comparisons using macro data, there is substantial aggregation bias and this is affecting our results. Third, measurement error in the capital stock may be correlated with education. Finally we consider the possibility that issues of functional form are of importance.

The fixed effects estimator will remove any endogeneity bias if the relevant unobservables are time-invariant. The GMM estimator uses lags of levels and first-differences of inputs as instruments to additionally control for time varying productivity shocks. While our diagnostics support the use of these instruments, there are other sets of instruments that can be exploited. In particular, we need to address concern that education may be correlated with

unobservables to such an extent that assuming it is exogenous severely biases our results. The results of these checks are presented in Columns 1, 2 and 3 of Table 2.6 and in Table 2.7. The key conclusion from these robustness checks is that the instrumenting procedure is not changing our view about the shape and relative magnitude of the return to education coefficients. We take three alternative additional instrument sets to address the possible endogeneity of education: using lags of education in the GMM style, using input prices, and using education supply and worker background information.

Column 1 exploits the time variation in the education measure available for Ghana to instrument for E in the system GMM style.¹⁴ This is not only a check of our instrumenting procedure, but also that the averaging of the education measure carried out for Ghana has not biased our results. The implied return on education in Ghana is, as it was in Table 2.2, low and insignificant when education is assumed to be endogenous. Thus, at least in Ghana, the exogeneity assumption is not causing significant bias in our estimate of the return to education. If one believes that the correlation between education and unobservables is similar in the two countries then this implies that the exogeneity assumption is also unproblematic for South Korea. Alternatively, one may believe that the types of unobservable factors important in South Korea are fundamentally different. If this is true and these are causing the South Korean estimate on E to be substantially biased upwards then this merely reinforces our conclusion. Skills are used in very different ways across the two economies - it is just that the factors that are

¹⁴Instrumenting both the linear and quadratic terms in education caused some instability in the estimates so only the linear term, capturing the average return to education, is included.

associated with this different use of skills are unobserved.

In Columns 2 and 3 of Table 2.6 we again assume that education is endogenous and use firm level wages and an index of material prices as additional instruments (in South Korea there are separate indices for imported and non-imported materials). The prices faced by the firm will be correlated with input choices but, assuming competitive markets, they will be uncorrelated with firm specific unobservables. The estimates were unstable when the quadratic term was included, and so it was dropped. These alternative instruments are accepted by the Sargan tests. The coefficients on inputs are of a very similar pattern and magnitude to those in Table 2.2 (where the coefficients in Table 2.6 are interpreted as the linear average of the quadratic return). The only substantive difference is that the coefficient on E in South Korea is higher (although so is its standard error).

We have been considering firms at the level of the aggregate manufacturing sector. While most firms are from sub-sectors common to both countries, it may be that the aggregation of sub-sectors is causing substantial bias. In order to check for this we restricted the analysis to include only those firms in the textiles and garments sector. The results are presented in Columns 4 and 5 of Table 2.6 and show the same pattern of coefficients across countries within this common sub-sector. While the restricted sample has resulted in some less precise identification we see that the return to education is low and convex in Ghana and high and concave in South Korea, and that the coefficient on materials is much higher in Ghana and the coefficient on labour inputs correspondingly lower. That these results hold even when restricted to a sector that is common between the countries, and is known to be highly

globalised, gives us confidence that the differences we observe are not a result of differing sectoral composition in the samples.¹⁵

We also have data for Ghana on the number of years of schooling and the occupation of the mother and father of some workers, and on the distance the worker was from the nearest primary school when six years old and from the nearest secondary school when twelve years old. These background measures will be uncorrelated with unobserved firm productivity, but correlated with education; for example, a worker with professional parents living near a secondary school will likely have more education than the child of farming parents with no nearby schools.¹⁶ These individual level variables are aggregated using the same process described earlier for worker education. The results of including these additional instruments with time-varying education are presented in Table 2.7. As they are only available for a subset of the firms and years, the OLS and standard GMM estimates for the same sub-sample are presented for comparison. It can be seen that the substantive pattern of input coefficients and TFP is unchanged, as that the return to education remains low and insignificant. For each estimator we also present the results when only the linear term in education is included. This enables us to confirm that, for all specifications, the magnitude of the return to education is low and the instrumenting is not changing our view.

As a further check on the likelihood that the exogeneity assumption on

¹⁵One could say that it is no surprise that firms are heterogenous across countries even within a narrowly defined sector. However the assumptions made by much of the literature based upon Equation 2.1, such as fixed β and a value added technology, imply that firms are using identical technology (as we define it) across countries *and* across sectors. Our microeconomic evidence demonstrates that this is potentially problematic.

¹⁶If firms and motivated households both choose to locate in areas with many schools then doubt would be thrown upon these particular instruments.

education is material we extracted the time-varying component of the error term (i.e. residual minus the fixed effect) from the fixed effect regressions of Table 2.2. Recall that education is effectively excluded from these regressions as our measure is time-invariant. Using this error as the dependent variable an OLS regression with education (linear and quadratic terms) as independent variables produced small and highly insignificant coefficients. This suggests that education is not correlated with time-varying unobserved productivity shocks.¹⁷

Tables 2.2, 2.6 and 2.7 have used lagged inputs, input prices and education supply variables respectively as instruments for average schooling. Imagine that one were to object to all these instruments and take the view that our estimates of differences in the return to education are purely the result of endogeneity bias. It is difficult to sustain the view that endogeneity is important in Ghana as even the OLS estimate of the return to education is low. Hence one would need to believe that firm level unobservables are highly correlated with education in South Korea, but not in Ghana. This would reinforce our view that the way in which firms in the two countries use education is a key determinant of output per worker differences.

The third possible concern is that the capital stock is mismeasured in a way that is correlated with the education of workers in the firm, for example, if firms in South Korea use more computers and this is not reflected in the price indices. Accurate measurement of the capital stock is difficult and it would be preferable to test for whether capital is a consistent aggregate if

¹⁷The correlation between the error term and education is less than 0.01 in absolute value in both countries.

such data were available. But note that differences in the composition and quality of the capital stock will be an element of technological difference and differences in the return to education on this basis would be consistent with our results.

Finally our analysis could be generalised by considering different functional forms. Table 2.3 presents the estimations when education is included as a logarithmic effect rather than a quadratic effect and, again, the same pattern of coefficients is observed. While other work using these data sets has concluded that the Cobb-Douglas functional form is appropriate [Söderbom and Teal, 2004, Hallward-Driemeier et al., 2002] it may be that this is too restrictive a specification. The Cobb-Douglas functional form is a first-order logarithmic Taylor series approximation with the translog being the second-order extension by including interaction terms between inputs. The translog production function has the problem that it is not globally concave and that output elasticities differ by input combination making interpretation more cumbersome. However, estimating the translog and evaluating the elasticities implied in Table 2.2 at the sample mean for each country did not change our conclusions. In fact, as the Cobb-Douglas is a restricted version of the translog, finding difference in the former is a stronger conclusion than finding it in the latter.¹⁸ We also experimented for Ghana with making labour input a CES aggregate of the quantities of skilled and unskilled labour and respective worker education. Again, this did not change our view on the return to education.

¹⁸The exception to this would be if there was a common translog production function and Ghanaian and South Korean firms are merely using different factor combinations (say due to differences in factor prices). This was tested for and easily rejected.

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

Table 2.8: Relative comparisons using the data in Hall and Jones[1999].

2.6 Why Does Productivity Differ?

In Table 2.1 we showed the very large differences in labour productivity between South Korean and Ghanaian firms. These differences greatly exceed those implied by the macro data which underlie the calculations of Hall and Jones [1999]. Table 2.8 shows the results from their paper for Ghana and South Korea where both are ranked relative to the US. This macro data suggests that labour productivity differs by a factor of seven times. While a large difference, this is much smaller than the difference in value added per worker of forty times in Table 2.1. In the Hall and Jones decomposition shown in Table 2.8 by far the most important factor in explaining this productivity differential is TFP which is nearly three times higher in South Korea than Ghana. This figure is close to the difference we observe in TFP across the firms in the two countries for the gross output specification where we do not control for education. The key to our result is that the return to education differs across the two countries by a very large amount.

There has been an extensive discussion in the literature on the return to education suggesting that the rises that can be found for some periods in the US and UK are due to skill biased technical change [Card and DiNardo, 2002]. Our data suggest that the much higher levels of capital per employee,

which reflect in part the far greater sophistication of the technology used in South Korea relative to that in Ghana, is associated with a much higher return to that education. Such a result is wholly consistent with those who have argued that rises in the return to education within developed countries can be explained by the rapid rate of technical progress in those economies. Our results are also consistent with work in developing countries which finds a convex return to education based on individual labour market data [Bigsten et al., 2000, Kingdon and Unni, 2001, Duraisamy, 2002].

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

If we use Equation 2.16 above and apply the GMM parameter estimates from Table 2.2 we can calculate the implied value added equation. We obtain for Ghana:

$$\begin{aligned}\frac{dV_{it}}{V_{it}} &= \frac{1}{(1 - 0.81)} \left[0.05 \frac{dK_{it}}{K_{it}} - (1 - 0.05 - 0.81) \frac{dL_{it}}{L_{it}} + 0.014 dE_{it} \right] \\ &= 0.26 \frac{dK_{it}}{K_{it}} - 0.71 \frac{dL_{it}}{L_{it}} + 0.074 dE_{it};\end{aligned}\tag{2.18}$$

and for South Korea:

$$\begin{aligned}\frac{dV_{it}}{V_{it}} &= \frac{1}{(1 - 0.49)}[0.16\frac{dK_{it}}{K_{it}} - (1 - 0.16 - 0.49)\frac{dL_{it}}{L_{it}} + 0.152dE_{it}] \\ &= 0.31\frac{dK_{it}}{K_{it}} - 0.69\frac{dL_{it}}{L_{it}} + 0.298dE_{it}.\end{aligned}\tag{2.19}$$

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

$$V_{it} = K_{it}^{\beta}(A_{it}H_{it})^{(1-\beta)}.\tag{2.20}$$

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

$$\frac{V_{it}}{L_{it}} = [\frac{K_{it}}{L_{it}}]^{\beta}e^{\delta h}.\tag{2.21}$$

For Ghana and South Korea we have, respectively:

$$\frac{V_{it}}{L_{it}} = [1.3]^{0.3}e^{0.074*10} = 2.3 \quad \text{and} \quad \frac{V_{it}}{L_{it}} = [61]^{0.3}e^{0.298*12} = 122.\tag{2.22}$$

This produces approximately the forty fold difference in the value added per employee across the firms in the two countries and consistent with the observed differences in medians in Table 2.1.

The mean years of education do not differ markedly between the two countries, ten and twelve years respectively. What does differ markedly, and can be clearly seen in Figure 2.2, is the shape of the (firm level) return to education function and the average return. In Ghana this is a very flat convex function, while in South Korea it is a concave function. The return in Ghana is much lower: even with the convexity the return does not reach 10% until the 15th year of education, while the average return over the observed range is 1-2%. A South Korean firm will be most productive when its workers have had 16.4 years of education, while Ghanaian firms only begin experiencing a positive return to education once their workers have more than 7.7 years of education.

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

Why are Ghanaian firms unable to capitalise on more educated workers? One explanation could be that Ghanaian education is a completely different input to South Korean education and that sitting for a year in a Ghanaian classroom will not have the same marginal effect as sitting for a year in a South Korean classroom. This is undoubtedly true, but even if the return to education function could be compressed in Ghana (so that education moves workers along it more rapidly) there is still a big gap to close. The evidence

from macroeconomic aggregate production function models is that various methods of incorporating schooling quality do not reduce cross-country unexplained TFP [Caselli, 2005]. Lower quality of education is unlikely to be the whole story.

A second explanation is that Ghanaian firms need to change the way in which they use education. These results suggest that education is not that useful in the material-intensive type of technology used by Ghanaian firms. The return to education in Ghana, and therefore the potential for gains in observed productivity or output per worker, could be substantially lifted if they used the more capital-intensive South Korean technology. This will require investment in physical capital stocks as well as the acquisition or development of external intellectual property; so, understanding barriers to technology adoption and investment are key to understanding differences in output per worker. Investment in physical capital and sophisticated production processes would raise the return on education, and therefore the demand from firms and the incentives of individuals to acquire it.

Figure 2.3 is a scatter plot of value added per worker versus capital per worker for the two samples of firms. At the micro level this recreates what has been observed in the macro data. Ghanaian firms form a distinct cluster from their South Korean counterparts and the level gap in value added per worker is significant and is not closed by increases in capital intensity. While the macro data appeals to differences in TFP, our micro analysis suggests this gap can be explained by differences in technology: chiefly by differences in the return to education but partly by differences in the physical input coefficients.

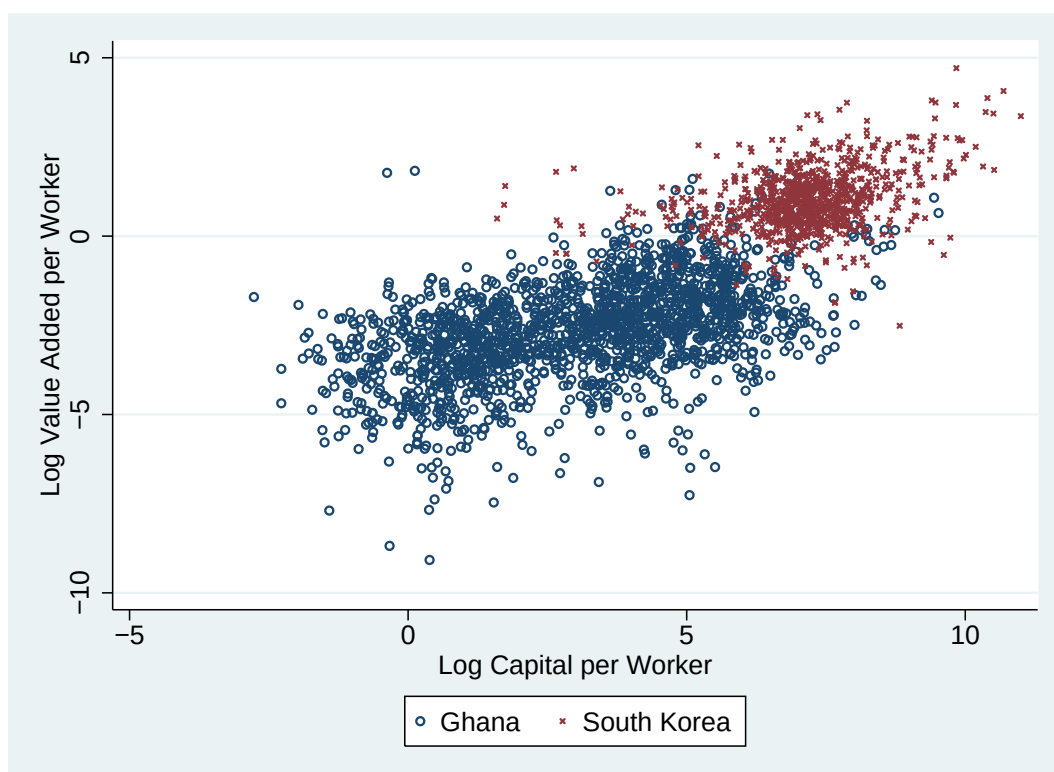


Figure 2.3: Value added and capital per worker expressed in 1996\$PPP.

Figure 2.3 is also suggestive that there is significant variation between firms within a country. Productivity may differ due to competitive pressures, R&D activities, export status, or a range of other factors. We do not discount that these factors are important in explaining between-firm variation, but it is remarkable that there is no average TFP difference between the countries even without taking into account any of these factors.

2.7 Concluding Remarks

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

There is an extensive macro literature seeking to explain cross-country differences in output per worker; however, these approaches have been unable empirically to capture the importance of labour quality. A number of authors have argued for the centrality of labour quality in understanding the global distribution of income, and we provide firm level microeconomic evidence to support such claims. Once we allow for technology and the return to education, an element of labour quality, to differ across countries, then the unexplained productivity differential becomes insignificant. The higher

output per worker in South Korean firms can be accounted for through a combination of factor intensity, technological difference and labour quality. It is these, not differences in TFP, that matter at the level of the firm.

Firms in Ghana do not receive much of a benefit from employing workers with more years of education, and so the demand for education is low. On average, giving a Ghanaian worker an extra year of education will increase output by 2% whereas giving a South Korean worker an extra year of education will increase output by 12%. As wages are linked to the change in a firm's output induced by hiring extra workers, this difference in turn reduces the incentive to acquire education.

The share of intermediate inputs is much higher in Ghana than in South Korea - 85% as opposed to just under 50%. This means that, for every unit of output produced, Ghanaian firms are spending relatively more on raw materials and relatively less on payments to workers and capital owners. These technological differences in the material-intensity of production and the return on skills are much more important than any differences in efficiency.

Poorer countries use a technology that is more intensive in its use of raw materials and less intensive in its use of capital and labour. Wages, the return to skills and the return on capital are lower with the material-intensive technology, and so understanding why firms choose to use it is important. The return to skills also differs across technologies with the return in poor countries being very low and possibly convex and the return in richer countries being high and concave. Accounting for differences in technology and in the return to skills can completely explain differences in output per worker across

firms in Ghana and South Korea. In Chapter 3, comparable firm level data sets from five African countries are used to investigate heterogeneity within Africa: with particular focus on the role of skills, input substitutability, the returns to scale and technological change.

2.A Data Appendix

The Ghanaian data used in this thesis 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.¹⁹ The questionnaire was designed by a team from the World Bank. The surveys have been funded by the Department for International Development of the UK Government and the CSAE is funded by the Economic and Social Research Council of the UK.

The data used are 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. The Ghanaian data was collected in a series of interviews with firm management and cover the period

¹⁹This program was organised by the World Bank and funded by the Belgian, British, Canadian, Dutch, French and Swedish governments. Extensions to this data for Ghana were collected by a team from the Centre for the Study of African Economies, Oxford and the Ghana Statistical Office (GSO), Accra over a period from 1992 to 2003. The surveys have been funded by the Department for International Development of the UK government. The Kenyan, Nigerian and Tanzanian data collection was funded by both DFID and UNIDO. Work on this project was funded by the Economic and Social Research Council of the UK as part of the Global Poverty Research Group.

1991-2002. Along with the survey questionnaire, this data is publicly available from the Centre for the Study of African Economics at the University of Oxford. The data set (including definitions and variable construction) is that used in Söderbom and Teal [2004] with the addition of the more recent survey rounds. The data used to estimate the production function are the value of physical capital stocks, number of employee-hours (number of employees multiplied by average weekly hours), expenditure on materials and other inputs (mostly electricity, other energy and rented land, buildings and equipment) and average firm worker years of education. There are also price indexes for output and material inputs used to convert the variables into real 1991 domestic currency prices. Gross output is measured as total sales, adjusted by changes in inventories.

The South Korean data were collected in face-to-face interviews covering 1996-1998, and are described in Hallward-Driemeier [2001]. The data and the survey questionnaire are publicly available from the World Bank. Output is calculated as sales plus the change in inventories. 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 et al., 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.

2.B Value Added vs Gross Output Production Functions

Biases from value added production functions can come from a failure to meet the technical separability conditions, imperfect competition [Basu and 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 then 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:

$$A_{GO} = \frac{Y}{F(K, L, M)}, \text{ or, } A_{VA} = \frac{Y - M}{V(K, L)}. \quad (2.23)$$

The functions V and F can have a number of forms; for example, 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:

$$\Delta A_{GO} = \frac{\frac{Y + \Delta Y}{F(K, L, M)}}{\frac{Y}{F(K, L, M)}} = 1 + \frac{\Delta Y}{Y} \quad (2.24)$$

$$\Delta A_{VA} = \frac{\frac{Y + \Delta Y - M}{V(K, L)}}{\frac{Y - M}{V(K, L)}} = 1 + \frac{\Delta Y}{Y - M}. \quad (2.25)$$

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 multi-factor productivity improvement is being attributed to a subset of the inputs. If we interpret the functions F and V as production functions, 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 $\frac{\Delta M}{Y-M}$.

The value added specification is given by:

$$\ln V = \ln a + b_K \ln K + b_L \ln L, \quad (2.26)$$

$$V = Y - M. \quad (2.27)$$

In an econometric context, consider what the bias will be if the true model is given by Equation 1.2 but we estimate Equation 2.26 (assume that labour is quality adjusted). The first order conditions for profit maximisation can be derived by taking the derivatives of a 3-factor gross output production function with respect to prices and then solving the three resulting simultaneous equations for the input quantities of K , L and M . Letting p_R represent the price of factor R we have:

$$M = \left(\frac{Y}{A} \left(\frac{p_K}{\beta_K} \right)^{\beta_K} \left(\frac{p_L}{\beta_L} \right)^{\beta_L} \left(\frac{\beta_M}{p_M} \right)^{\beta_K + \beta_L} \right)^{\frac{1}{\beta_K + \beta_L + \beta_M}}. \quad (2.28)$$

Assuming constant returns to scale for simplicity, and because that restriction

is not rejected by our data, we write Equation 2.28 as $M = \gamma \frac{Y}{A}$. In order to understand the bias in the coefficients in Equation 2.26 we want to express the true model in a form that corresponds to the incorrect model and then compare coefficients. Repeated substitution of Equation 1.2 into Equation 2.26, using Equations 2.27 and 2.28, gives:

$$\begin{aligned}
\ln V &= \ln Y + \ln\left(1 - \frac{M}{Y}\right) \\
&= \ln Y + \ln\left(1 - \frac{\gamma}{A}\right) \\
&= \ln A + \beta_K \ln K + \beta_L \ln L + \beta_M \ln M + \ln\left(1 - \frac{\gamma}{A}\right) \\
&= \ln A + \beta_K \ln K + \beta_L \ln L + \beta_M [\ln Y - \ln A + \ln \gamma] + \ln\left(1 - \frac{\gamma}{A}\right) \\
&\vdots \\
&= \ln A + \frac{\beta_M}{1 - \beta_M} \ln \gamma + \ln\left(1 - \frac{\gamma}{A}\right) + \frac{\beta_K}{1 - \beta_M} \ln K + \frac{\beta_L}{1 - \beta_M} \ln L.
\end{aligned} \tag{2.29}$$

In a 3-factor model with constant returns to scale, the bias in the value added coefficients will therefore be as follows:

$$\ln a = \ln A + \frac{\beta_M}{1 - \beta_M} \ln \gamma + \ln\left(1 - \frac{\gamma}{A}\right), b_K = \frac{\beta_K}{\beta_K + \beta_L}, b_L = \frac{\beta_L}{\beta_K + \beta_L}. \tag{2.30}$$

2.C Dynamics and the System GMM Estimator

The system GMM (sGMM) estimator developed by Blundell and Bond [1998] was a major tool used in the empirical investigation in Chapter 2. In this appendix the system GMM estimator and the application to the models and

data of this thesis is presented in more detail. Generalised method of moments estimation has increasingly become a preferred way to estimate panel data models. Arellano and Bond [1991] note that in some cases it is more realistic to restrict the serial correlation structure of the errors than to assume strict exogeneity. Based upon this premise, the system GMM estimator has been developed to remove endogeneity bias in panel data, without imposing homoskedasticity or other distributional structure on the error term. Finding exogenous instruments uncorrelated with fixed effects or error components with sufficient power is often difficult, and the spirit of the GMM estimators is to exploit moment conditions in differences, lags and levels of the variables to overcome this problem.

GMM estimation makes use of the panel dimension of the data to use lagged values of variables as instruments. The difference GMM (dGMM) estimator takes first differences to remove the firm fixed effect, then uses lagged levels as instruments for contemporaneous differences. Arellano and Bond [1991] describe how the initial condition restriction $E(x_{i1}e_{it}) = 0 \forall t = 2, \dots, T$ leads to the moment restrictions $E(x_{i,t-s}\Delta e_{it}) = 0$ being available for estimation. This is valid for $s > 2$ if $e_{it} \sim MA(0)$ and for $s > 3$ if $e_{it} \sim MA(1)$. Thus, lagged levels can be used as instruments for the differenced equation, as they will be correlated with contemporaneous differences but uncorrelated with the error. However, it is well documented that this method performs poorly in a highly autoregressive panel or as $\frac{Var(\mu_i)}{Var(e_{it})}$ increases [Blundell and Bond, 1998]. In an extreme case where y_{it} is a white noise process, contemporaneous differences are completely uncorrelated with lagged levels. The finite sample bias in the dGMM estimator with weak

instruments resulting from an AR(1) process is in the direction of the FE estimator.

Arellano and Bover [1995] consider a different GMM estimator. With the initial condition restriction $E(\eta_i \Delta y_{i2}) = 0$, along with the further condition of the first difference of inputs being uncorrelated with the fixed effect, i.e. $E(\eta_i \Delta x_{it}) = 0$, the moment conditions $E((\eta_i + e_{it}) \Delta x_{i,t-s}) = 0$ are valid for $s = 1$ if $e_{it} \sim MA(0)$ and for $s = 2$ if $e_{it} \sim MA(1)$. Thus, similarly to the difference GMM estimator described above, lagged differences then become valid instruments for equations in levels. Blundell and Bond [1998] show that the bias and inefficiency of the dGMM estimator can be reduced by estimation in conjunction with a levels equation. The combination of these two methods is known as the sGMM estimator and is particularly appropriate for panels where N is large and T is small. A further advantage of sGMM over dGMM is that, as it includes a level equation, fixed costs are implicitly incorporated.

The number of moment conditions available varies depending upon whether the model is a dynamic or static specification and whether explanatory variables are thought to be strictly exogenous, predetermined or endogenous, which will be tested. For example, if the explanatory variables x_{it} are predetermined, they will be uncorrelated with future and current errors and correlated with past errors i.e. $E[x_{is}e_{it}] = 0$ if $s = 1, \dots, T; t = 2, \dots, T$ and

$E[x_{is}e_{it}] \neq 0$ otherwise. This leads to the following moment conditions:

$$E[y_{i,t-s}\Delta e_{it}] = 0 \quad \text{for } t = 3, \dots, T \text{ and } 2 \leq s \leq t-1; \quad (2.31)$$

$$E[x_{i,t-s}\Delta e_{it}] = 0 \quad \text{for } t = 3, \dots, T \text{ and } 1 \leq s \leq t-1; \quad (2.32)$$

$$E[e_{it}\Delta y_{i,t-1}] = 0 \quad \text{for } t = 3, \dots, T; \quad (2.33)$$

$$E[e_{it}\Delta x_{it}] = 0 \quad \text{for } t = 2, \dots, T. \quad (2.34)$$

The sGMM estimator has both one- and two-step variants, which are not equivalent unless $\sigma_\mu^2 = 0$. The one-step method imposes *a priori* a weight matrix that does not depend on unknowns in the regression, whereas the two-step version estimates this weight matrix from a first stage regression. The two-step standard errors are corrected using the finite sample bias correction developed by Windmeijer [2000]. The common factor restrictions and the constant returns to scale hypothesis are also conducted on this basis. While the two-step version is more efficient, inference conducted on the basis of the one-step estimates has been shown to be more reliable [Blundell and Bond, 2000] and so, although both variants were estimated, the one-step versions are presented in this thesis.

Consider now the application of the sGMM estimator to the estimation of production functions. Blundell and Bond [2000] also consider a Cobb-Douglas production function; however, their production system is specified

as:

$$\begin{aligned}
y_{it} &= \beta_l l_{it} + \beta_k k_{it} + \alpha_t + (\eta_i + v_{it} + m_{it}), \\
v_{it} &= \gamma v_{i,t-1} + e_{it} & |\gamma| < 1, \\
e_{it}, m_{it} &\sim MA(0).
\end{aligned} \tag{2.35}$$

In this system y is log sales, l is log employment, k is log capital stock, γ_t a year specific intercept, η_i a firm fixed effect, v_{it} autoregressive productivity shocks and m_{it} serially uncorrelated measurement errors. This generalises in the obvious way to the set of explanatory variables that were used in Table 2.1. This is a more general specification than the static model outlined in Section 2.2, where the small time dimension of the South Korean data led us initially to pursue a static specification. In Equation 2.35 the shock v_{it} is autoregressive. It can be shown that an AR(1) process such as this is equivalent to an MA(∞) process, where the current realisation of v_{it} depends on all past realisations $e_{i,t-s}$, $s = 1, \dots, t$. In order for the moments used in the system GMM estimator to be valid in the static specification, that is without the inclusion of a lagged dependent variable, stronger assumptions than those made in Blundell and Bond's example need to be made.

What are these additional assumptions that need to be made for the static model to be valid? Consider a production function system analogous to Equation 2.35 without specifying a particular structure on the error process:

$$y_{it} = \beta_x x_{it} + \alpha_t + \eta_i + v_{it}. \tag{2.36}$$

How deep do lags of the endogenous variables need to be in order to become valid instruments? We seek an instrument for an endogenous variable $x_{i,t}$, that is, one which is correlated with $x_{i,t}$ but uncorrelated with the contemporaneous error $v_{i,t}$. The Arellano-Bond [1991] statistic is a test of autocorrelation in the differenced residuals. In first differences we would expect to see negative autocorrelation in the differenced residuals as, for example, $\Delta v_{i,t}$ and $\Delta v_{i,t-1}$ both share a $v_{i,t-1}$ term even if there is no autocorrelation in levels. Hence a finding of AR(1) using the Arellano-Bond statistic is uninformative in the GMM estimates; however, is meaningful for the OLS where there is no differenced equation. For the GMM estimates, a finding of AR(2) in differences is indicative of AR(1) in levels, and so on. If there was no AR(1) in levels then, for an endogenous variable, lags $x_{i,t-2}$ and further could be used as instruments in the differenced equation. If there is AR(1) in levels, or AR(2) in differences as tested by the Arellano-Bond statistic, then $x_{i,t-2}$ will be endogenous to $v_{i,t-2}$ and therefore also to $v_{i,t-1}$ and so will be an invalid instrument for $x_{i,t}$ in the differenced equation. Thus we would need to take lags $t-3$ and deeper to get valid instruments.²⁰

So, assuming AR(2) in differences, the lagged instruments dated $t-3$ and earlier will be valid and we are taking the moment conditions:

$$E[x_{i,t-j}\Delta v_{it}] = 0 \text{ for } t = 4, \dots, T \text{ and } j \geq 3. \quad (2.37)$$

²⁰In the language of the `xtabond2` command in Stata, this would necessitate specifying the suboption `gmm(endogvars, lag(3 .))`.

This is equivalent to assuming:

$$E[v_{i,t-j}\Delta v_{it}] = 0 \text{ for } t = 4, \dots, T \text{ and } j \geq 3, \quad (2.38)$$

when x is endogenous.²¹ If this condition does not hold, then the relevant lagged levels and differences of the right hand side variables will not be valid instruments for the static specification. Such a restriction would exclude a process as in Equation 2.35 as that specification makes the errors an MA(∞) process, so the current error is dependent upon all past errors. In Section 2.4 the stronger assumptions embodied in Equation 2.37 were made because of the small time dimension of the South Korean data. For Ghana we have up to 12 years of data per firm, and so we can investigate the robustness of our results to imposing stronger structure on the error term. In this section we consider dynamics of the form considered by Blundell and Bond and examine the dynamic specification given in Equation 2.35.

Following Blundell and Bond [2000], Equation 2.35 has a dynamic representation:

$$\begin{aligned} y_{it} = & \beta_l l_{it} - \gamma \beta_l l_{i,t-1} + \beta_k k_{it} - \gamma \beta_k k_{i,t-1} + \gamma y_{i,t-1} \\ & + (\alpha_t - \gamma \alpha_{t-1}) + (\eta_i(1 - \gamma) + e_{it} + m_{it} - \gamma m_{i,t-1}). \end{aligned} \quad (2.39)$$

Augmenting this with our time-invariant measures of education, this is equivalent to running the unrestricted regression and imposing $\pi_2 = -\pi_1\pi_5$ and $\pi_4 = -\pi_3\pi_5$. These are known as the common factor (comfac) restrictions.

²¹We also require the usual assumptions $E[\eta_i] = E[v_{it}] = E[\eta_i v_{it}] = 0$ along with the initial conditions $E[y_{i1}v_{it}] = 0$ for $t=2, \dots, T$.

Equation 2.39 then becomes:

$$y_{it} = \pi_1 l_{it} + \pi_2 l_{i,t-1} + \pi_3 k_{it} + \pi_4 k_{i,t-1} + \pi_5 y_{i,t-1} + \pi_6 E_i + \pi_7 E_i^2 + \alpha_t^* + \eta_i^* + w_{it}. \quad (2.40)$$

Again, the system extends trivially to the case of more than two inputs. Equation 2.40 will exhibit constant returns to scale if $\sum_i \pi_i = 1$. Imposing constant returns to scale and including a time-invariant measure of education leads to the estimating equation:

$$\begin{aligned} y_{it} - l_{i,t-1} = & \pi_1 (l_{it} - l_{i,t-1}) + \pi_3 (k_{it} - l_{i,t-1}) + \pi_4 (k_{i,t-1} - l_{i,t-1}) \\ & + \pi_5 (y_{i,t-1} - l_{i,t-1}) + \pi_6 E_i + \pi_7 E_i^2 \\ & + \alpha_t^* + \eta_i^* + w_{it}. \end{aligned} \quad (2.41)$$

The estimate of π_2 can then be recovered using the CRS restrictions, and that of the coefficient on E by the appropriate non-linear combination (ie $\frac{\pi_6}{(1-\pi_5)}$ for E and similarly for E^2). The long-run coefficients can be obtained by allowing all variables to be constant, for example, $k_{it} = k_i \forall t$. This implies that the long-run coefficient on capital, β_K in our previous notation, is given by $\frac{\pi_3 + \pi_4}{1 - \pi_5}$.

The dynamic production function from Equation 2.41 for South Korea presented in Table 2.9, and the associated long-run parameters in Table 2.11, is not very informative. Due to the lack of available lags in the South Korean data, the instruments in the GMM system for the dynamic specification will only be valid if all explanatory variables are predetermined.²² This assump-

²²If x_{it} is predetermined then $E(x_{it}v_{is}) = 0$ for $s \geq t$ and $E(x_{it}v_{is}) \neq 0$ for $s < t$. Compared to the endogenous case, we are making the additional moment restriction

tion is questionable on an *a priori* basis so, even though the instrument set is accepted by the Sargan test, we view the GMM estimates with suspicion. This is especially the case given that the Sargan test will have weak power with so few degrees of freedom. Blundell and Bond [2000] show that the OLS estimate of π_5 in Equation 2.40 should be biased upwards, while the equivalent within groups estimate should be downward biased. The OLS estimate on the lagged dependent variable is very close to one and the FE estimate is actually negative, although so imprecise so as to be not significantly different from zero.

The GMM estimate of π_5 in Table 2.9 is also very close to one and is not significantly different from the OLS estimate. This is suggestive that the GMM instrumentation is not producing consistent estimates in the dynamic South Korean case. In fact, the GMM point estimates taken as a whole are imprecise, not robust between specifications and the implied long-run coefficients are implausible. Neither current nor lagged levels of capital or labour are significant, nor is any education term. The comfac restrictions are marginally accepted which, with the level of imprecision in the estimates, is only weak evidence in support of this restriction. While it is clear that the GMM instrumenting procedure is not effective in this case, even the implied long-run coefficients from the OLS are implausible and imprecise. The South Korean data is not producing reasonable estimates in the dynamic case, likely due to the small time dimension. Thus we restrict attention in the South

$E(x_{it}v_{is}) = 0 \forall s = t$. If the lags appropriate for an endogenous variable are used then the number of instruments equals the number of regressors and so the equation is exactly identified, but these estimates are extremely imprecise and of unrealistic magnitudes and their validity cannot be tested so this approach is not presented.

Korean case to the estimates from the static specification.

Turning now to the Ghanaian estimates in Table 2.10 we see that the coefficient on the lagged dependent variable is less than one even in the OLS estimates and greater than zero even in the FE estimates. The GMM estimate is comfortably between the two, suggesting that the GMM estimator is dealing successfully with the dynamic biases in the data. While the Sargan statistic accepts the instrument set for both GMM estimates, the ones with the t-3 instrument set are to be preferred. This is because of the evidence of AR(2) in differences, or AR(1) in levels, which means that we need to take an extra lag to find suitable instruments for our endogenous regressors. The common factor restrictions are rejected which suggests that the structure given in Equation 2.35 is not appropriate for the Ghanaian data. The long-run coefficients presented in Table 2.12, including the return to education as well as the other input parameters, are remarkably robust across specifications, and also very similar to those from the static specification in Table 2.2. This suggests that any bias from dynamic processes is not severely biasing the static estimation with appropriate lags; leading us to conclude that the static estimates are consistent.

In system GMM the number of instruments is an important parameter. Too many instruments can result in overfitting and also weakens the power of the Sargan test [Bowsher, 2002]. The number of instruments is not reported, but can be easily calculated. The degrees of freedom of the Sargan test is $j - k$ where j is the number of instruments and k is the number of regressors. Thus the number of instruments can be calculated by the addition of the reported degrees of freedom of the Sargan test and the number of regressors

(including the constant).

For the instruments used in the system GMM estimator to be valid, they of course need to be exogenous. In the case where the number of instruments exceeds the number of instrumented variables the system is over-identified and the usual Sargan statistic can be used to test the joint validity of the moment conditions. Where the errors are not homoskedastic or are auto-correlated the Sargan statistic is inconsistent and the Hansen J test should be used as it is equivalent to a robust Sargan statistic [Roodman, 2006]. These two terms are used interchangeably, and refer to the Sargan test when homoskedastic errors are being assumed and the Hansen statistic otherwise.

The system GMM estimators were designed with dynamic panel data models in mind, more specifically, for panel data models with a lagged dependent variable. These GMM techniques do, of course, have uses in other contexts as well, but we should explain why this estimator is generally implemented without a lagged dependent variable in this thesis. A sufficient, but stronger than necessary, set of conditions for the GMM estimator to be valid without a lagged dependent variable is if the error terms are uncorrelated over time. How likely is this to hold *a priori* in the data being used here? The South Korean panel has the minimum feasible time dimension ($T=3$) for the use of the system GMM estimator. In fact, including a lagged dependent variable means that we cannot have any endogenous variables and we have to assume all variables are predetermined. In any estimation, the large sample properties of the estimators may not hold in the particular empirical sample even if the underlying data generation process exhibits those properties. For example, the empirical correlation between a sample from each of

two uncorrelated random variables will be unlikely to be zero. With such a low T-dimension the results of tests on the South Korean data will be highly dependent upon the particular finite sample properties and may not necessarily reflect the true underlying parameters. Given that one of these time periods is lost to differencing leaving effectively two sequential observations, and that the autocorrelation tests find no evidence of even AR(1), assuming no autocorrelation in the residuals seems acceptable for the South Korean data.

For Ghana we have a much larger panel - up to twelve years of data for some firms. This allows us to give a more comprehensive consideration to the role of dynamics in the production function. The fact that the comfac restrictions are rejected indicates that the particular structure given by the system in Equation 2.35 does precisely describe the evolution of the residuals. However, the significant and reasonable estimate of the coefficient on the lagged dependent variable in the GMM t-3 estimates tell us that it is clear that dynamics are playing a role. The question that needs to be asked is how far does our specification need to diverge from a static OLS estimation in order to provide consistent estimates given the dynamics involved? The two major issues we are concerned about are endogeneity of the explanatory variables and inconsistency resulting from autocorrelation in the residuals. The estimates that deal most comprehensively with these two issues are the GMM t-3 estimates in the dynamic specification. The implied long-run coefficients from this equation will be consistent in the presence of the widest range of properties in the residuals. The static specification implies some extra restrictions on the dynamic relationship in the residuals (namely, those

given by Equation 2.37); however, the estimates from the static estimations are not statistically different from those in the full dynamic specification, and nor are they different in a qualitative sense. The autocorrelation tests in the static specification provide evidence that there is AR(1) but no AR(2) in the levels residuals, and thus that the restrictions of Equation 2.37 are not rejected. Further evidence supporting the use of those instruments comes from the relevant Sargan statistics. Thus we conclude that there is limited gain from allowing for a more general form of autocorrelation in the errors, as given by the dynamic specification, and so we proceed using the static estimates for simplicity and consistency with the South Korean treatment. Use will still be made of the OLS, FE and GMM estimators to correct for endogeneity.

Other evidence suggests that firms in Ghana have been stagnant over this period and that dynamic processes have not been playing a major role. In a review of the evidence from studies drawing on a decade of enterprise and firm surveys in Africa, Bigsten and Söderbom [2005] conclude that “Africa’s own manufacturing sector is small and stagnant, and undertakes little investment” and that “technology transfer to Africa’s manufacturing sector is slow”. The low rates of investment, growth and technology transfer are consistent with the assumption of dynamic processes not being important in Africa.

As a final note, consider the scenario where there are measurement errors in the data. If there is AR1 and a lagged dependent variable is included in the presence of measurement errors, then this produces a MA process in the errors. This means that, to get valid instruments, a further lag needs to be taken. When the measurement error is given by $y - y^*$, where y is observed

and the true value y^* is unobserved, we have:

$$y_{it}^* = \gamma y_{it-1}^* + \beta x_{it} + \eta_i + v_{it}; \quad (2.42)$$

$$y_{it} = y_{it}^* + m_{it}; \quad (2.43)$$

$$y_{it} = \gamma y_{it-1} + \beta x_{it} + \eta_i + (v_{it} + m_{it} - \gamma m_{it-1}). \quad (2.44)$$

If there was no lagged dependent variable included in this model, the measurement errors of the past do not come into the current equation (as the AR1 is in the v_{it}), but this period's v_{it} will be an average of all past $v_{i,t-s}$. This is equivalent to the situation in Equation 2.35 and so the previous analysis applies. In the event that the strict AR1 process in Equation 2.35 does not apply and there are measurement errors, then the inclusion of a lagged dependent variable will be needlessly introducing an MA(1) process into the errors.

	OLS	FE	GMM
y_{t-1}	0.9369*** (0.0278)	-0.0272 (0.1029)	0.9178*** (0.1894)
E	0.1325 (0.1116)		0.2347 (0.1841)
E^2	-0.0049 (0.0043)		-0.0090 (0.0069)
k_t	0.0184 (0.0401)	0.0309 (0.0456)	-0.0242 (0.0655)
k_{t-1}	-0.0064 (0.0402)	-0.0086 (0.0476)	-0.0569 (0.0423)
l_t	0.1955* (0.0784)	0.2553** (0.0774)	0.1264 (0.1017)
l_{t-1}	-0.1935* (0.0793)	0.1522 (0.1001)	-0.1504 (0.1384)
i_t	0.1716*** (0.0303)	0.2247*** (0.0402)	0.1899*** (0.0417)
i_{t-1}	-0.1571*** (0.0320)	0.0439 (0.0596)	-0.1024 (0.0721)
m_t	0.2390*** (0.0417)	0.2266*** (0.0380)	0.2728*** (0.0514)
m_{t-1}	-0.2044*** (0.0414)	0.1022 (0.0670)	-0.1730* (0.0781)
Constant	-0.6823 (0.7033)	5.0851*** (0.8244)	-1.1983 (1.1976)
Comfac	0.2515	0.0569	0.0851
AR1	0.6200		
Sargan			11.28
Sargan df			10
Sargan p			0.3359
Obs	560	560	560
Firms		320	320
CRS	0.8924	0.0001	0.8437

Table 2.9: Dynamic production function for South Korea imposing CRS. Comfac is a p-value from a test of the restrictions embodied in Equation 2.40. Note that the AR(2) test requires $T \geq 5$ and so cannot be computed for any specification, and the AR(1) statistic cannot be calculated for the dynamic GMM where we need $T \geq 4$. With three time periods, there is only one lag available for use in the instruments and so this restricts us to the case where all explanatory variables are predetermined. Year dummies were included but are not reported. Other notes as in Table 2.2.

	OLS	FE	GMM t-2	GMM t-3
y_{t-1}	0.6166*** (0.0304)	0.3462*** (0.0246)	0.4109*** (0.0665)	0.5409*** (0.0731)
E	-0.0403 (0.0211)		-0.0550 (0.0339)	-0.0341 (0.0324)
E^2	0.0028* (0.0012)		0.0039 (0.0020)	0.0028 (0.0020)
k_t	0.0108 (0.0125)	0.0090 (0.0141)	0.0562 (0.0292)	0.0523 (0.0328)
k_{t-1}	-0.0005 (0.0116)	-0.0049 (0.0147)	-0.0229 (0.0277)	-0.0413 (0.0301)
l_t	0.0925*** (0.0219)	0.1068*** (0.0192)	0.0582 (0.0539)	0.1443* (0.0601)
l_{t-1}	-0.0500* (0.0217)	-0.0019 (0.0192)	-0.0004 (0.0505)	-0.0984 (0.0566)
i_t	0.1460*** (0.0265)	0.1088*** (0.0109)	0.1224*** (0.0356)	0.1286* (0.0644)
i_{t-1}	-0.0776*** (0.0195)	-0.0343*** (0.0103)	-0.0472 (0.0246)	-0.0613 (0.0542)
m_t	0.6018*** (0.0406)	0.6523*** (0.0106)	0.6437*** (0.0317)	0.6201*** (0.0406)
m_{t-1}	-0.3395*** (0.0385)	-0.1819*** (0.0183)	-0.2211*** (0.0433)	-0.2851*** (0.0621)
Constant	0.7528*** (0.1349)	1.1760*** (0.0787)	1.0712*** (0.2488)	0.7761** (0.2593)
Comfac	0.0000	0.0000	0.1007	0.0229
AR1	0.5949		0.0000	0.0000
AR2	0.6122		0.0203	0.0673
AR3	0.0151		0.1010	0.1316
Sargan			168.8	149.5
Sargan df			173	153
Sargan p			0.5756	0.5640
Obs	1598	1599	1598	1598
Firms		240	239	239
CRS	0.0398	0.0727	0.7406	0.5535

Table 2.10: Dynamic production function for Ghana. For further notes see Tables 2.2 and 2.9.

	OLS	FE	GMM
k_t	0.1895 (0.1956)	0.0217 (0.0637)	-0.9867 (2.5152)
l_t	0.0328 (0.2731)	0.3967*** (0.1028)	-0.2922 (2.1257)
i_t	0.2297 (0.1800)	0.2614** (0.0753)	1.0649 (2.5765)
m_t	0.5481*** (0.1748)	0.3202*** (0.0727)	1.2139 (2.0660)
E	2.1015 (1.8610)		2.8548 (6.2558)
E^2	-0.0771 (0.0722)		-0.1092 (0.2475)

Table 2.11: Implied long-run coefficients on inputs for South Korea from the estimates in Table 2.9.

	OLS	FE	GMM t-2	GMM t-3
k_t	0.0268 (0.0156)	0.0063 (0.0170)	0.0567* (0.0272)	0.0239 (0.0329)
l_t	0.1108*** (0.0217)	0.1604*** (0.0235)	0.0982** (0.0287)	0.0999* (0.0440)
i_t	0.1784 *** (0.0288)	0.1138*** (0.0174)	0.1276*** (0.0312)	0.1464*** (0.0476)
m_t	0.6840*** (0.0355)	0.7195*** (0.0176)	0.7175*** (0.0366)	0.7298*** (0.0586)
E	-0.1050*** (0.0540)		-0.0934 (0.0551)	-0.0743 (0.0683)
E^2	0.0074*** (0.0031)		0.0066* (0.0033)	0.0062 (0.0041)

Table 2.12: Implied long-run coefficients on inputs for Ghana from the estimates in Table 2.10.

Chapter 3

Technological Change in Africa

In this chapter the analysis turns to a comparison of five African countries to investigate heterogeneity within Africa, with a translog generalisation of the production function allowing a particular focus on the role of skills, input substitutability, the returns to scale and technological change. There is intracontinental variation in technology; however, its magnitude is much less than the intercontinental variation. The pattern of Chapter 2 holds within Africa as well. As GDP per capita rises, the share in total inputs of materials, which are found to be substitutable with other inputs, falls, while the return to education increases. Accounting for these elements, there are no significant differences in total factor productivity in Africa. In this chapter we argue that firms in poorer countries prefer to use a different technology because of the flexibility afforded by using a greater share of variable rather than fixed inputs. In this chapter we show a potential mechanism through which improved institutions and investment climate can lead to higher living standards; that is, through facilitating changes in technology.

3.1 Introduction

African firms are very different from firms in East Asia and, on many measures, they are not as successful. They are, on average, smaller, use different factor proportions, different technology, face different factor prices and have different qualities of inputs (including human capital). Chapter 2 showed that output per worker differentials between Ghanaian and South Korean firms result from a difference in production technology and a difference in the firm level return 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. Technology and the return to education in African firms are the focus of this chapter and we investigate how firms differ within the continent. This information is used to further inform understanding of the cross-continental comparison. We show a potential mechanism through which improved institutions and investment climate can lead to higher living standards, that is, through facilitating technology choice.

Section 3.2 develops a model of the global family of technologies which can be tested against the results from the various production functions. Section 3.3 asks the question “does technology differ between countries within Africa?” This is answered by taking a pooled data set with samples of manufacturing firms from five African countries and estimating Cobb-Douglas production functions for each. The hypothesis of technological heterogeneity, using the understanding of the term developed in Chapter 2, is then tested. Estimates of the return to worker education are also obtained. The patterns of technological difference within Africa will be shown to form a co-

herent narrative with the differences that have been observed between Africa and elsewhere.

Section 3.4 generalises the Cobb-Douglas specification of Section 3.3 and introduces some dynamics into the production function to allow for a more precise characterisation of the production process. The translog form will allow us to ascertain if technology is truly distinct between countries and if there is an expansion path which will move the characteristics of African firms closer to those in South Korea. Having concluded that technology is indeed distinct and systematically linked with development, we will then consider the role of education and material use.

Using the results from this and the previous Chapter, some possible motivations for firms to choose heterogeneous technologies are developed in Section 3.5. We hypothesise that Ghanaian firms prefer to use their existing technology as it is less risky. In the event of a downturn they can simply reduce production and cease purchasing raw materials, in contrast to the opportunity cost of capital which, in the short run, must be paid regardless of output. Section 3.6 concludes this chapter.

3.2 A Global Model of Technology

What is the process governing the transformation of manufacturing sectors from the material intensive, low productivity, low return to human capital structure that we observe in Ghana to the capital intensive, high productivity, skill intensive production systems of South Korea? A model of such change can be built using empirical and theoretical innovations from the ag-

gregate production function literature and the results of Appendix 2.B. The parameterisation of the aggregate value added production function is generally assumed to be constant across countries [Hall and Jones, 1999], yet a long tradition of appropriate technology models argues that production techniques vary widely across countries. This apparent contradiction can be resolved using the results of Appendix 2.B. The technological heterogeneity of the appropriate technology literature is a gross output phenomena, that is, one of the actual production process. The homogeneity argued for by, among others, Hall and Jones [1999] can then be explained as a value added phenomena, and is really a comment on relative income shares rather than on technology and production techniques. The final piece of structure needed is a functional form. Microfoundations for the Cobb-Douglas production function are given by Jones [2005], who demonstrates that, if the distribution of ideas follows a Pareto distribution, the aggregate production function will be Cobb-Douglas. Thus the specific characterisation of the world technology frontier should be given by:

$$\begin{aligned}
\ln Y &= \alpha_k + \sum_{Q=K,L,I,M} \beta_Q^k \ln Q + \phi^k(E) & (3.1) \\
\sum_{Q=K,L,I,M} \beta_Q^k &= 1 \\
\beta_K^k : \beta_L^k &= 0.3 : 0.7,
\end{aligned}$$

where the k index refers to a particular technology (as used by firms in a particular country) and E is a measure of human capital, which will again be schooling in this chapter. Constant returns to scale is not a necessary

imposition; however, theory suggests that it would be observed in long-run equilibrium. In this chapter we present production function estimates for five countries (Ghana, Kenya, Nigeria, South Africa and Tanzania) which, along with the results for South Korea in Chapter 2, can then be used as evidence to evaluate this hypothesis.

3.3 Technology Across the Continent

Technology differs between firms in Ghana and those in South Korea and now we consider within-Africa differences. Are there different technologies being used within Africa? Can we find any African countries, such as South Africa, which are using the South Korean technology? What can the existence and form of any heterogeneity within Africa tell us about how a transition to a ‘larger’ technology may occur? By interacting input coefficients with a dummy variable, we also test for heterogeneity across sector, foreign ownership and export status. Variation by firm size is not addressed here as it can be incorporated into the generalised technology in Section 3.4.

Table 3.1 summarises the pooled unbalanced panel on manufacturing firms from five countries used in this chapter, which were collected as part of the RPED as described in Section 2.A. 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, textiles, garments, wood, furniture, and a sector consisting of South African textile and garment firms. The econometric starting point for the analysis is a 4-factor gross output Cobb-Douglas production function, as in Chapter 2, where the output of firm i at time t , Y_{it} , is a function of physical capital K_{it} , human capital $e^{\phi(E_{it})}L_{it}$ (itself a function of average worker years of schooling E and number of workers L), raw material inputs M_{it} , indirect costs I_{it} , total factor productivity α_t and other firm specific factors, possibly including firm fixed effects, X_{it} . The basic specification is thus given as:

$$\ln Y_{it} = \alpha_t + \beta_K \ln K_{it} + \beta_L \ln L_{it} + \beta_I \ln I_{it} + \beta_M \ln M_{it} + \phi(E_{it}) + \delta X_{it}. \quad (3.2)$$

The function ϕ is taken to be quadratic in E and the vector X consists of firm age, a dummy taking the value 1 if the firm exports, a dummy taking the value 1 if the firm has any foreign ownership, and dummies for the country and sector in which the firm operates. A firm fixed effect is sometimes incorporated into X .

The term ‘technology’ refers to the magnitude of the coefficients β and the function ϕ . If these differ between countries then it is said that firms in the two countries use a different technology. More specifically, if the parameters of ϕ differ then it is said that the way in which skills are used is the dimension in which technology differs. Total factor productivity is given by α and it is allowed to differ over time. In the specification of Equation 3.2, all elements of the vector X of firm characteristics affect output only through adjusting

TFP. There are many papers in the literature dealing with the effect of such characteristics on TFP [Bigsten et al., 2004, Clerides et al., 1998, Tybout et al., 1991]. These variables, which are known to affect TFP, are included so that the differences in unexplained TFP can be compared.

3.3.1 Heterogeneity Within Africa

The form of technology and the return to education are the two key differentials between manufacturing firms in Ghana and those in South Korea. Table 3.2 presents Cobb-Douglas production functions for the five African countries in our data set.¹ 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 export status and sector proved insignificant, while that for foreign ownership was significant but quantitatively small. 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.

¹A dynamic production function, as in Arellano and Bond [1991] and Appendix 2.C, was also investigated and is consistent with the results presented here.

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

Table 3.1: Summary statistics for the African Data. The variable definitions are taken from Rankin et al. [2006]. Employment is the total number of employees in the firm. Output, capital, raw material and indirect costs are all in 1996 PPP\$. The deflation procedure used for Ghana, Kenya and Tanzania was to deflate the nominal values into constant price domestic and then convert into PPP\$ using the exchange rates in the Penn World Tables. The deflation for both Ghana and Tanzania used firm based price indices while for Kenya sector level deflators were used. In the case of Nigeria and South Africa, the nominal values were deflated by consumer prices (producer prices being unavailable) then converted in US\$ using the exchange rate for the base period. These US numbers were then deflated by the PPP deflator to 1996 values. Firm age is in years and any foreign ownership is a dummy which takes the value 1 if the firm has any element of foreign ownership and zero otherwise. Exports is a dummy taking the value 1 if the firm exports, and Educ is the weighted average of years of education of workers in the firm. The Ghanaian data is described more fully in Chapter 2 and the Nigerian data in Malik et al. [2006]. Most of this data is available at www.csae.ox.ac.uk. These summary statistics were calculated over those observations with data on all variables and so those regressions without the full set of variables may include some additional observations. Note also that the standard error of the mean, given in parenthesis, can be converted into the standard deviation of the variable through multiplying by $\sqrt{N}$.

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

Table 3.2: The dependent variable is log of real output in 1996\$PPP. Cobb-Douglas production functions for five African countries. Constant returns to scale have been imposed and the p-value testing this from the unrestricted regression is given as CRS. Food and Bakeries is the omitted sector, and Ghana is the omitted country dummy. Year dummies were included but are not reported. TechDiff is a p-value from a test of technological difference: for GKN the null is no difference from each other, for Tanzania and South Africa it is no difference from GKN. Standard errors are robust to heteroskedasticity and autocorrelation, and use a clustering method that allows for the errors to be correlated within firms.

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

3.3.2 Skills

The results obtained when a quadratic education term is included are presented in Table 3.3. For each of the two technologies for which we have education data three sets of estimates are presented. The first is a simple OLS estimation, which was shown in Chapter 2 to be acceptable for the analogous modelling done in that paper, with the measure of education varying by firm. The second treats education as a firm fixed effect: the annually reported worker education levels for each firm are averaged so that the measure is time-invariant (recall this is the approach taken in Table 2.2). This has the effect of reducing variance in the education measure. Such an approach will be preferred if one believes that there is significant measurement error in the education data, or if that human capital embodied in a firm is a long-term characteristic and so will not be contemporaneously affected by the yearly fluctuations in the number of years of schooling of the employees. The third column adapts this approach by including a firm fixed effect along with the

time-varying measure of education.

Table 3.3 shows no significant level TFP difference between the countries (as given by the intercept term), and that the return to education (to the firm) is low in Africa. In Tanzania the effect of education is never significantly different from zero. For GKN, education is only significant when it is treated as time invariant and then it is as in Table 2.2: small in magnitude and slightly convex. There is unfortunately no human capital data available for the South African firms but we can impute a rate of return which would be consistent. The intercept for South Africa in Table 3.2 is 1.2 higher (in logs) than that of the other countries. Assuming an average of 10 years of education for workers in South African manufacturing firms, then an average linear coefficient of 0.1 would close the gap (ie approx. 10% return on each year of schooling). This figure is midway between the corresponding figures for South Korea and Ghana presented in Chapter 2. The rate of return that we would need to impose so that South Africa was perfectly consistent with the proposed structure of technology appears plausible.

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

	T OLS	T Av OLS	T FE	GKN OLS	GKN Av OLS	GKN FE
lnK	0.034*** (0.010)	0.033** (0.010)	0.066* (0.028)	0.071*** (0.009)	0.066*** (0.010)	0.140*** (0.018)
lnL	0.113 (0.013)	0.114 (0.013)	0.151 (0.028)	0.119 (0.015)	0.125 (0.015)	0.129 (0.01)
lnI	0.267*** (0.025)	0.266*** (0.026)	0.209*** (0.025)	0.163*** (0.014)	0.159*** (0.014)	0.127*** (0.010)
lnM	0.587*** (0.021)	0.587*** (0.021)	0.575*** (0.022)	0.647*** (0.018)	0.649*** (0.018)	0.605*** (0.010)
E	-0.008 (0.026)	-0.000 (0.036)	-0.052 (0.037)	-0.022 (0.024)	-0.116* (0.047)	0.018 (0.021)
E ²	0.001 (0.002)	0.001 (0.002)	0.003 (0.002)	0.001 (0.001)	0.007* (0.003)	-0.001 (0.001)
Exports	0.034 (0.041)	0.032 (0.041)		0.063 (0.034)	0.064 (0.034)	
Anyfor	-0.033 (0.042)	-0.035 (0.043)		0.040 (0.039)	0.046 (0.038)	
Firm Age	-0.001 (0.001)	-0.001 (0.001)	-0.059 (0.105)	0.003* (0.001)	0.003* (0.001)	-0.070 (0.126)
MetMac	-0.047 (0.038)	-0.050 (0.038)		0.017 (0.042)	0.020 (0.041)	
Textile	-0.098* (0.046)	-0.098* (0.046)		-0.062 (0.049)	-0.057 (0.049)	
Garment	-0.057 (0.051)	-0.056 (0.051)		0.034 (0.046)	0.041 (0.045)	
Wood	0.028 (0.064)	0.029 (0.064)		-0.006 (0.067)	-0.001 (0.064)	
Furn	-0.056 (0.047)	-0.058 (0.048)		0.062 (0.054)	0.074 (0.053)	
Kenya				-0.092* (0.046)	-0.068 (0.046)	
Constant	2.134*** (0.145)	2.105*** (0.165)	3.483 (1.777)	2.124*** (0.153)	2.533*** (0.239)	3.558 (2.665)
Educ	0.444	0.357	0.354	0.537	0.037	0.702
Obs	715	715	715	2090	2090	2090
Firms			297			516

Table 3.3: The dependent variable is log of real output in 1996\$PPP. Cobb-Douglas production functions for 3 African countries including a quadratic education effect. Constant returns to scale have been imposed. Firms reporting average worker education of over 15 years were excluded. Columns 1 and 4 are OLS estimates, while columns 2 and 5 use the (time invariant) average level of education for each firm. Columns 3 and 6 are fixed effect estimates. Other notes as for Table 3.2.

3.4 A More General Specification

The Cobb-Douglas functional form is a relatively simple form widely used in empirical analysis; however, it imposes a number of restrictions on technology. For example, output elasticities are constant across all input combinations. This restrictive functional form may be artificially generating technological difference when the true difference lies in scale or factor choice. If elasticities of substitution between inputs vary with scale then a Cobb-Douglas functional form may reject the hypothesis of common technology whereas a more general form may not. In the context of a Cobb-Douglas production function, a firm cannot embark on a transition along the path identified in Section 3.3 through increases in scale or factor proportions - it must shift to a new production function. The translog production function allows for output elasticities to vary with scale under a common technology. Here we see if the technological heterogeneity identified in Chapter 2 is robust to generalisation.

3.4.1 The Translog Production Function

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

$$\ln Y_{it} = a_t + \sum_{r=1}^n b_r \ln q_r + \frac{1}{2} \sum_{r=1}^n \sum_{s=1}^n c_{rs} \ln q_r \ln q_s + \delta X_{it}. \quad (3.3)$$

For ease of notation, q_r is used to represent the quantity of inputs $r = 1, \dots, n$. The input coefficients, which we use to describe the technology of

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

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

There are a number of ways in which human capital can be incorporated into the production function. The most simple is as a pure level effect, as modelled in Table 3.3. However, that method does not consider possible in-

interactions with the production function coefficients, which the results so far suggest are often important. Human capital may be incorporated into the technology through its inclusion as a completely separate input or through an appropriate transform of the labour quantity input. The latter approach is pursued here so as to prevent the production function becoming too cumbersome, although there is some loss of generality in doing so. The particular transform used multiplies the number of workers by the average years of education of workers at the firm before taking the natural logarithm.²

Technological Progress

We allow for aggregate TFP growth over time through the inclusion of year dummies. Trends in technology can affect individual factors at different exponential rates (i.e. linear in logarithmic terms). A further test investigates whether Hicks-neutral technological progress, where the coefficient is the same on each input, holds. Such linear characterisations of technology are clearly inappropriate over very long time horizons and need to be viewed as linear approximations over the time period concerned. $\sum_{r=1}^n d_r$ will indicate if the returns to scale are changing over the time period. If this quantity is positive, then it is indicative that returns to scale in African manufacturing are increasing in magnitude over time and could be the source of secular productivity gains. The second-order, technology-adjusted translog production function is then:

$$\ln Y_{it} = a_t + \sum_{r=1}^n b_r \ln q_r + \frac{1}{2} \sum_{r=1}^n \sum_{s=1}^n c_{rs} \ln q_r \ln q_s + \sum_{r=1}^n d_r t \ln q_r + \delta X_{it}. \quad (3.4)$$

²Note this is implicitly assuming a linear return to education.

Properties of the Production Function

The translog functional form allows the testing of various properties of a production function. These properties include the Cobb-Douglas form, homogeneity, returns to scale, separability, technical progress and the value added specification. It is clear by inspection that, if all the c_{rs} are zero, Equation 3.4 reduces to the familiar Cobb-Douglas form.³ Using the definition that a function f is homogenous of degree θ if $f(tX) = t^\theta f(X)$ it follows that a translog production function will be homogenous of degree θ if $\sum_{r=1}^n b_r = \theta$ and $\sum_{r=1}^n c_{rs} = 0 \forall s$. If, in addition to homogeneity, $\theta = 1$ the function also exhibits constant returns to scale or, equivalently, linear homogeneity. More generally, for a homogenous function, θ is an estimate of the returns to scale of the technology.

Tables 2.2 and 3.2 show that firms in different countries use different technologies but all operate under constant returns to scale. The translog framework allows for this result to be probed in more detail.⁴ For example, it is possible that the same non-homogenous translog production function underlies firms in both countries, or that technology is only CRS on average. For a non-homogenous function output elasticities will differ with input combinations. So, given that South Korean firms use substantially different input combinations (in this scenario perhaps due to factor prices), it is possible that incorrectly approximating with a Cobb-Douglas function will give the appearance of different technologies. If this is the case, then we would

³ $Y = A q_K^{b_K + d_K t} q_L^{b_L + d_L t} q_I^{b_I + d_I t} q_M^{b_M + d_M t}$, where $A = e^a$.

⁴Note that, although the tests are not presented for reasons of brevity, the same country groups of technology difference persist in the translog.

expect African firms to look like those in South Korea as their input ratios and levels become more like those of South Korean firms. Alternatively, if the technology is homogenous but of degree significantly greater than unity any noted increases in input levels could lead to productivity convergence. If hypotheses such as these turn out to be supported, then the policy relevance is not with technology choice, but with increasing the scale of African firms and ensuring that factor prices are not distorted. However, at the other extreme, if African firms are using a linearly homogenous technology, then a technological switch will be required.

Production functions also have a set of separability properties. Two inputs r and s are said to be weakly separable from a third input k if $\frac{\partial}{\partial q_k} \frac{\frac{\partial f}{\partial q_r}}{\frac{\partial f}{\partial q_s}} = 0$; that is, if the marginal rate of substitution between a pair of inputs is independent of the levels of all other inputs. In the translog framework this condition reduces to $c_{rk} = c_{sk} = 0$.⁵ If inputs are found to be separable then restrictions can be placed upon the functional form to improve the efficiency of the analysis. Analogous definitions hold for global separability (where all inputs are separable from each other) and pairwise separability. The most relevant form of pairwise separability is that of capital and labour from materials and indirect inputs. This is a necessary, but not sufficient, condition for a value added specification to be valid. Thus testing of this particular form of pairwise separability will indicate whether the value added specification should be investigated.

⁵Technically this condition is sufficient but not necessary; however, the conditions under which it is not necessary are restrictive enough that they can be ignored. The necessary and sufficient conditions are that $s_s c_{rk} - s_r c_{sk} = 0$ and $c_{si} c_{rk} - c_{ri} c_{sk} = 0 \forall i$. As factor shares s_r and s_s must be positive it is clear how the sufficient condition noted above follows.

The translog form will also allow some comment to be made upon substitution between inputs. While there is no unambiguous definition of the elasticity of substitution in a multi-input framework (see Appendix 3.A), any measure of substitutability will be dependent upon the cross-derivative of output with respect to the two inputs. This, in the translog framework, will be the coefficient on the interaction term c_{rs} . Comparing the signs of the cross-derivatives will indicate how the marginal productivity of one input is affected by changes in the input level of another. For example, if this coefficient was positive, it would be evidence to suggest that the inputs are complements. An increase in the level of input r would then increase the marginal productivity of input s which, in turn, would *a priori* cause the optimising firm to increase the level of input s . This second indicator of the elasticity properties is of course not dependent upon input levels, but does provide an intuitive reason as to why consideration of the second derivative is an appropriate way to consider substitution possibilities.

3.4.2 Results

The results from the translog are presented in Tables 3.4, 3.6, 3.5 and 3.7. Overall, the diagnostics suggest that the OLS and FE estimates are to be preferred for Tanzania, and the OLS and GMM estimates are to be preferred for GKN. For the Tanzanian GMM estimation, the monotonicity and quasi-concavity do not hold for most of the observations and the implied MPL is too low. For GKN we suspect that the FE estimates are biased due to the high MPK. The GMM instruments are theoretically valid if there is no

	Tanz OLS	Tanz FE	Tanz GMM	GKN OLS	GKN FE	GKN GMM
b_K	-0.0059 (0.0504)	-0.0954 (0.1893)	-0.1182 (0.1387)	0.2263*** (0.0475)***	0.2062** (0.0716)**	0.1039 (0.1012)**
b_L	0.1330 (0.0866)	0.0721 (0.1850)	0.0006 (0.3016)	0.2258 (0.0494)	0.1973 (0.0720)	0.3176 (0.1120)
b_I	0.7690*** (0.1129)	0.8470*** (0.1598)	0.7010* (0.3194)	0.2497*** (0.0691)	0.2209*** (0.0627)	0.4447*** (0.1159)
b_M	0.0217 (0.0972)	0.1649 (0.1544)	0.1501 (0.2294)	0.2981*** (0.0721)	0.3756*** (0.0698)	0.1338 (0.1197)
c_{KK}	0.0071 (0.0090)	0.0401 (0.0214)	0.1019* (0.0396)	0.1026*** (0.0168)	0.1195*** (0.0175)	0.1119*** (0.0262)
c_{LL}	0.0253 (0.0286)	0.0575 (0.0362)	-0.0562 (0.0853)	0.0200* (0.0081)	0.0129 (0.0128)	0.0298 (0.0188)
c_{II}	0.1121** (0.0351)	0.1433* (0.0673)	-0.0246 (0.0824)	0.0789*** (0.0115)	0.0602*** (0.0103)	0.0923*** (0.0188)
c_{MM}	0.1604*** (0.0273)	0.1764*** (0.0371)	0.0954 (0.0562)	0.1481*** (0.0189)	0.1296*** (0.0145)	0.1544*** (0.0280)
c_{KL}	0.0144 (0.0126)	-0.0146 (0.0189)	0.0402 (0.0391)	0.0192** (0.0070)	0.0017 (0.0117)	0.0049 (0.0151)
c_{KI}	-0.0105 (0.0124)	-0.0192 (0.0209)	-0.0729* (0.0372)	0.0045 (0.0069)	0.0042 (0.0071)	0.0004 (0.0106)
c_{KM}	-0.0009 (0.0100)	-0.0010 (0.0165)	-0.0450 (0.0325)	-0.0513*** (0.0126)	-0.0628*** (0.0128)	-0.0212 (0.0156)
c_{LI}	0.0096 (0.0252)	0.0120 (0.0440)	0.1208 (0.0740)	-0.0129 (0.0086)	-0.0061 (0.0089)	0.0029 (0.0122)
c_{LM}	-0.0402* (0.0194)	-0.0283 (0.0318)	-0.1294** (0.0471)	-0.0263** (0.0088)	-0.0085 (0.0115)	-0.0377* (0.0165)
c_{IM}	-0.1180*** (0.0266)	-0.1541*** (0.0414)	0.0342 (0.0610)	-0.0705*** (0.0155)	-0.0584*** (0.0128)	-0.0956*** (0.0237)
Cons	2.9083*** (0.2451)	4.0719 (2.8087)	3.3912*** (0.6366)	1.8855*** (0.1887)	3.0335 (1.8488)	1.9939*** (0.3451)

Table 3.4: The dependent variable is log of real output in 1996\$PPP. Input coefficients from an unrestricted translog production function. The errors for the OLS and fixed-effects estimators are corrected for intra-firm correlation using a clustering method. Based upon testing, lags dated t-2 and t-3 are used as instruments in Tanzania, while those dated t-3 and t-4 are used for GKN. Linear homogeneity was not rejected for GKN and so has been imposed. Standard errors are robust to heteroskedasticity and autocorrelation, and those for the OLS and FE regressions have been calculated using a clustering method that allows for the errors to be correlated within firms. These results continue in Table 3.5.

	Tanz OLS	Tanz FE	Tanz GMM	GKN OLS	GKN FE	GKN GMM
d_K	-0.0003 (0.0025)	-0.0066 (0.0042)	-0.0001 (0.0126)	-0.0061* (0.0027)	-0.0068* (0.0030)	-0.0030 (0.0048)
d_L	0.0067 (0.0049)	0.0149 (0.0086)	0.0361 (0.0209)	-0.0063 (0.0035)	-0.0091 (0.0052)	-0.0094 (0.0055)
d_I	-0.0308*** (0.0066)	-0.0268** (0.0087)	-0.0634 (0.0333)	0.0030 (0.0040)	0.0032 (0.0038)	-0.0095 (0.0084)
d_M	0.0193** (0.0064)	0.0174* (0.0084)	0.0342 (0.0267)	0.0084 (0.0045)	0.0105** (0.0035)	0.0219** (0.0069)
Exports	0.0016 (0.0398)	0.0099 (0.0551)	-0.0093 (0.0706)	0.0428 (0.0303)	-0.0222 (0.0362)	0.0522 (0.0510)
Anyfor	0.0047 (0.0366)		0.1467 (0.0750)	0.0281 (0.0376)		-0.0221 (0.0803)
Firm Age	-0.0010 (0.0009)	-0.0846 (0.1533)	0.0023 (0.0032)	0.0026** (0.0010)	-0.0566 (0.0884)	0.0050* (0.0022)
Metmac	-0.0088 (0.0310)		0.0186 (0.0541)	0.0795* (0.0362)		0.1072* (0.0436)
Textile	-0.0876* (0.0440)		-0.0645 (0.0968)	0.0153 (0.0401)		0.0528 (0.0527)
Garment	-0.0160 (0.0424)		-0.0083 (0.0744)	0.0744* (0.0375)		0.0787 (0.0560)
Wood	0.0170 (0.0534)		0.0899 (0.1024)	-0.0160 (0.0578)		-0.0065 (0.0715)
Furn	-0.0170 (0.0389)		-0.0116 (0.0729)	0.1446** (0.0457)		0.1770** (0.0565)
Kenya				-0.0469 (0.0471)		-0.1045 (0.0600)
AR1			0.0193			0.0000
AR2			0.1705			0.0009
AR3						0.0452
AR4						0.5321
Sargan			40.0019			163.1821
Sargan df			85			452
Sargan p			1.0000			1.0000
Obs	716	720	716	2105	2105	2105
Firms		302	298		516	516

Table 3.5: The dependent variable is log of real output in 1996\$PPP. These results continue from Table 3.4

AR(3), which is rejected at the 5% but not the 1% level. AR3 would render the instrument sets used invalid as three-period lags have been assumed to be uncorrelated with the contemporaneous unobservables. The Sargan test easily accepts the validity of the instruments; however, the test is weak and the high p-value is possible evidence of over-fitting. The instruments are not rejected by the testing, but they may be weak. The implied marginal products are reasonable for both the OLS and the GMM estimators. The monotonicity and quasi-concavity properties are also acceptable for these regressions. The Reset test, while not a direct test of endogeneity⁶, does not indicate omitted variables in the OLS. Thus for GKN we consider both the OLS and GMM estimators being mindful of the direction of possible bias in each. Chapter 2 carried out a more extensive analysis of endogeneity in the Ghanaian data and found that the patterns of the coefficients remain remarkably robust across a range of methodologies for correcting for endogeneity. For the purposes of this chapter it is generally not critical to know the exact magnitude of the coefficients, we are more interested in the overall pattern.

Table 3.6 presents average elasticities and marginal products for each input for each country and estimation technique. These are of interest not only in themselves, but can also be used as a robustness check. Teal [2000] reports that the average nominal wage for male manufacturing workers in

⁶The Reset test detects neglected non-linearities by testing for correlation between the error term and $\hat{y}^2$, $\hat{y}^3$, etc. If non-linear combinations of the estimated values help explain the error it is indicative of omitted variables correlated with the independent variables. However, there are patterns of correlation that give the Reset test the same distribution under the null and alternate and so the non-rejection of the null is not sufficient to indicate no endogeneity.

Ghana in 1996 was 95,181 Cedis per month, corresponding to 1996US\$698 per year. For a worker with the average ten years of education this gives an implied MPL almost identical to that from the GMM estimation in Table 3.6.⁷ Using the Tanzania Manufacturing Enterprise Survey conducted by the Centre for the Study of African Economies at the University of Oxford, median (mean) wages and total labour costs are \$422 (\$735) and \$602 (\$903) respectively. Given that workers have an average of seven years of education, these figures are consistent with the OLS and FE estimates; however, they suggest that the GMM estimates are incorrect. The return to capital (in terms of output) is estimated at 7% in Tanzania and 7%-10% in Ghana, and further suggests that the GKN FE estimates are biased as the implied return is too high. Note that there are no firms in either sample that exhibit output elasticities comparable to those of South Korean firms.⁸

Material Use

The input coefficients from the translog are presented in Table 3.4. The signs of the material cross-input terms are all negative, suggesting that materials are substitutable with all other inputs. The apparent substitutability of materials with other inputs is a major feature of the production function. This provides support for the idea that using a technology that is material-intensive provides African firms with more flexibility.

⁷Note further that the wage given by Teal [2000] for unskilled workers is 1996US\$422 per year. To be perfectly consistent with the GMM estimate in Table 3.6 unskilled workers would need to have 6.3 years of education. The corresponding figures for the OLS and FE estimates is 4.3 years.

⁸Specifically, there are no firms where the implied output elasticity of capital is greater than 0.10 and that of labour greater than 0.20.

	T OLS	T FE	T GMM	GKN OLS	GKN FE	GKN GMM
CapElas	0.0370	0.0571	0.0214	0.0590	0.1442	0.0538
LabElas	0.0913	0.0690	0.0272	0.0851	0.0793	0.0720
IndElas	0.5218	0.3880	0.8272	0.2312	0.2026	0.3674
MatElas	0.3572	0.4117	0.0866	0.6195	0.5628	0.5068
MPK	0.0718	0.0702	0.0387	0.0708	0.2497	0.1039
MPL	102.5888	59.8391	28.8855	98.6503	98.9142	66.1665
MPI	6.1434	4.0295	9.6806	2.6021	2.2940	4.1902
MPM	0.6885	0.7811	0.1504	1.2345	1.1190	0.9955

Table 3.6: Marginal products are calculated by multiplying the relevant elasticity by output per unit factor ie $MPX = \varepsilon_X \frac{Y}{X}$. Elasticities and marginal products are firm specific in a translog production function. Here the mean of elasticities and the median of marginal products is presented. The lack of direct concordance between elasticities and marginal products is due to the different distribution of ε_X in each estimation method and the non-normality of $\frac{Y}{X}$. Note the units of wages are employees per year weighted by education and so, for example, multiplying MPL by ten gives the implied marginal product for a worker with 10 years of education.

Taking the first derivative of Equation 3.4, it can be seen that for each input r the sum of the coefficients on the interaction terms, $\sum_s c_{rs}$, give what will happen to the output elasticities as input levels rise. The sum of these terms are given in Table 3.7. We do not reject the null that these are all equal to zero in GKN, and in Tanzania these are negative for intermediate inputs and positive for capital and labour. As the input levels of firms rise in Tanzania, we will observe a small reduction in the material and indirect inputs elasticity of output, and a rise in that of capital and labour. There is mixed evidence on the validity of a value added specification; however, even if the specification is valid for each sample separately, it does not follow that it is appropriate for comparison or that use of intermediate inputs does not differ by country. In particular, the test of weak separability used here is a test of whether the marginal rate of substitution between labour and capital

	T OLS	T FE	T GMM	GKN OLS	GKN FE	GKN GMM
CobbDouglas	0.0000	0.0000	0.0007	0.0000	0.0000	0.0000
Homog	0.0047	0.2960	0.0044			
LinHomog	0.0001	0.3668	0.0074	0.4139	0.0474	0.7564
GlobalSep	0.0000	0.0001	0.0053			
CapSep	0.5688	0.6224	0.0768	0.0008	0.0000	0.5810
LabSep	0.0631	0.4243	0.0157	0.0051	0.7078	0.1545
IndSep	0.0001	0.0027	0.1097	0.0000	0.0000	0.0000
MatSep	0.0000	0.0001	0.0036	0.0000	0.0000	0.0000
VAD	0.0925	0.7545	0.0054	0.0003	0.0000	0.1341
TechProg	-0.0051	-0.0012	0.0067	-0.0010	-0.0022	0.0000
Hicks	0.0003	0.0103	0.1883	0.0157	0.0002	0.0060
NoTP	0.0000	0.0016	0.1403	0.0304	0.0005	0.0124
Monot	0.9046	0.6729	0.3463	0.8456	0.9242	0.9074
Qconv	0.6566	0.2785	0.2514	0.6449	0.7763	0.7003
KInteract	0.0101	0.0053	0.0241			
LInteract	0.0092	0.0266	-0.0246			
IInteract	-0.0067	-0.0179	0.0575			
MInteract	0.0013	-0.0069	-0.0448			
Reset	0.1097			0.8020		
Hausman		0.0002			0.0010	

Table 3.7: Specification tests on an unrestricted translog production function. All entries are p-values unless otherwise specified. CobbDouglas is testing the null hypothesis that the production function is Cobb-Douglas. KInteract is the quantity $\sum_j c_{Kj}$, with similar definitions for other inputs. Homog is the null hypothesis of homogeneity of any degree, while LinHomog is the null hypothesis of linear homogeneity. GlobalSep tests the null that the production function is globally separable (equivalent to the test of Cobb-Douglas when linear homogeneity is imposed), while CapSep tests the null that capital is separable from other inputs with analogous definitions for other inputs (restricted to 0 when linear homogeneity is imposed). VAD test the null that capital and labour are jointly separable from other inputs. TechProg reports the magnitude of $\sum_i d_i$. Hicks tests the null of Hicks-neutral technical progress ($d_i = d\forall i$) while NoTP tests for $d_i = 0\forall i$. Reset is the p-value from a Ramsey Reset test with the null of no omitted variables. Hausman is a test of the null of random effects against the alternative of fixed effects. Thanks to Måns Söderbom for kindly providing some STATA code for the translog regularity tests.

is independent of other inputs. Even if this holds, it is still possible that the relationship between TFP and the level of intermediate inputs or the coefficients of the gross output production function will differ across or even within countries.

Technological Change

The translog production function contains a wealth of potential information, including some implications for technological change. Much useful data to this end is contained in Tables 3.5 and 3.7: most saliently, the coefficients d and the tests of technological progress. The contrast between Tanzania and GKN is particularly instructive. According to the Penn World Tables 6.2 over the period 1991-2003, the widest range in our data, real GDP per capita in Tanzania grew by a total of 132%. Of the countries in our sample the next highest growth rate was that of Ghana at 53%. Using PPP-adjusted GDP per capita as the measure, Tanzania was also the poorest country in the sample. At the start and end of the period its GDP per capita was 56% and 23% respectively below that of Nigeria, the next poorest. Note that the year dummies, although not reported for brevity, mirror this trend and show significant growth for Tanzania and no growth elsewhere.⁹ Tanzania also undertook substantial economic reforms in the 1990s. So we have the poorest country in our sample using a distinct technology and growing rapidly during a period of major economic reform - surely instructive for investigating

⁹The PWT data is for the whole economy whereas our data is only for manufacturing firms. The fact we see no TFP growth in firms in Ghana and Nigeria but some GDP growth suggests that the growth was in the non-manufacturing sectors of the economy, such as Cocoa or Oil.

technological change.

Looking at the coefficients d in Table 3.5 we can see that, for Tanzania, the major change over time has been a fall in the intensity with which ‘other inputs’ are used. More broadly, taken together, the share of raw materials and other inputs in production has been falling, while that of capital and labour has been rising. In GKN, where there was no substantial growth, the effects are the reverse. The absolute value of the statistic TechProg in Table 3.7 tells us how returns to scale have been changing over time and this effect has been small and likely negative. So the evidence from comparing the rapidly growing Tanzania with GKN is that there have not been changes in average returns to scale, but weight is shifting over time between the coefficients giving higher output elasticities of capital and labour as GDP per capita rises.

Returns to Scale

This is not to say that there is no interest in considering the returns to scale of the firms. The returns to scale are not necessarily constant in a translog production function and are a function of input quantities. The returns to scale exhibited by the technology will differ between firms using different, in either absolute or relative terms, levels of inputs. Thus we can use the estimated translog production function to calculate firm specific estimates of the returns to scale. Overall returns to scale are given by the summation of the partial derivatives of Equation 3.4 with respect to each input where these partial derivatives are evaluated at the observed input quantities of the firm. All other things being equal, the usual theoretical expectation would

be that smaller firms are more likely to exhibit increasing returns to scale (if some factor, such as a credit constraint, is restricting their growth) or, if technology is at least locally CRS, for there to be no relationship (as this is the equilibrium where no firms wish to contract or grow).

Testing, as presented in Table 3.7, indicates that linear homogeneity cannot be rejected in GKN and so it has been imposed. This necessarily restricts the returns to scale to be constant for all firms. However, no such restriction was imposed for Tanzania as there was evidence from the OLS and GMM estimates that technology may not be homogenous, let alone linearly homogenous. Thus, by using the estimates from Tables 3.4 and 3.5, we can evaluate the returns to scale for each firm individually in Tanzania. Figure 3.1 plots these estimates of the returns to scale versus the natural logarithm of average firm employment, which is taken to be a measure of firm scale. While linear homogeneity in GKN tells us that there is no relationship; for Tanzania, returns to scale are actually *increasing* in firm size.

The relationship in Figure 3.1 is the first instance where a constant returns to scale Cobb-Douglas production function has not been sufficient to model the production technology of firms. Larger firms are combining inputs together in a different way to smaller firms, and in a way which is producing greater economies of scale. We are able to pick up this effect in the translog model, which is necessarily absent in the Cobb-Douglas, because of the inclusion of the second order terms. How, then, could interactions between inputs be contributing to the differential returns to scale across firms? Take labour and materials as an example of an input pair. Recall that the coefficient c_{LM} is negative in Tanzania. This implies that materials and labour are substi-

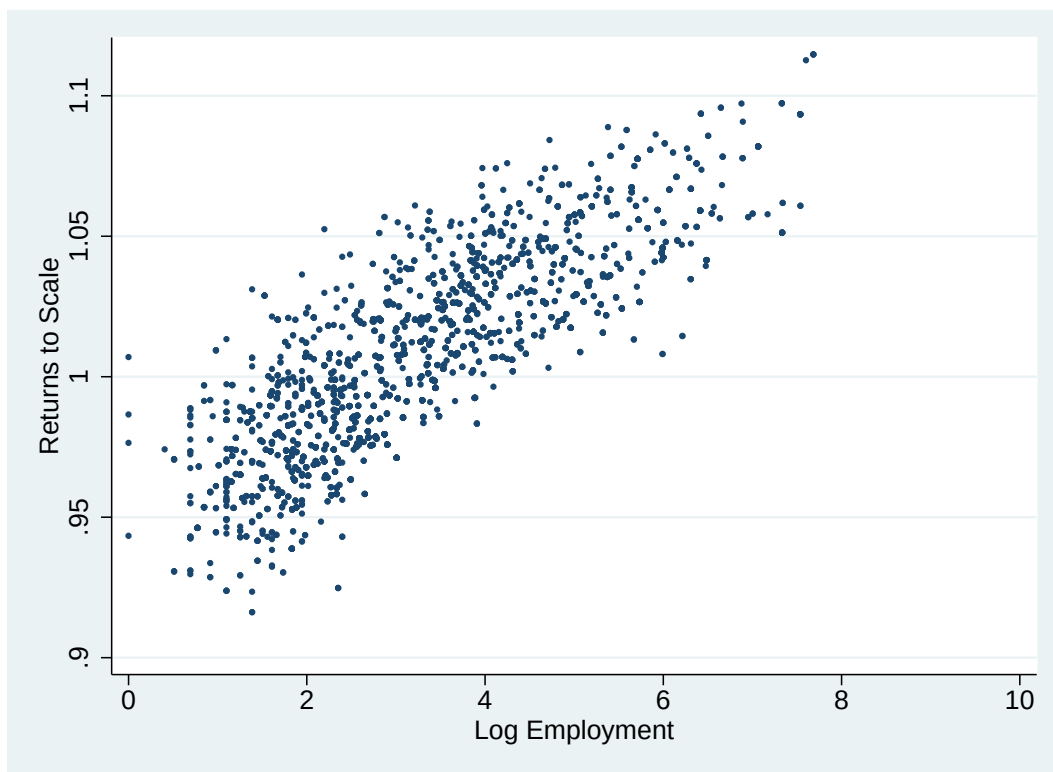


Figure 3.1: Returns to scale vs Employment in Tanzania.

tutes in production. Labour intensive manufacturing involves workers taking raw materials and, using capital and other inputs, transforming them into a final good. There is more scope for workers to specialize in a larger firm and so the efficiency with which they perform this transformation of raw materials will increase. A firm will then find larger investments in fixed inputs profitable and will wish to expand output so that its newly specialized workers can be fully occupied in the single task in which they have now developed a comparative advantage. Thus, with a translog technology, the manner in which inputs are combined will lead to increases in returns to scale.

This is consistent with Tanzanian firms, as they grow, moving to a point where they switch from a technology intensive in the use of variable factors to one intensive in the use of fixed factors. Continuing the example of the previous paragraph, a firm may be able to switch to a more specialized set of production machinery. As they near the point where they want to switch they face capacity constraints using their existing technology and so we see increasing returns to scale. Note that if a Cobb-Douglas production function were imposed in Tanzania, such as in Table 3.2, the non-linearities in inputs would express themselves as firm specific TFP increasing in firm size. In Tanzania we have shown that the production technology of the firm, rather than TFP, is the source of this gain.

3.5 Understanding Technology

In this section the results of Chapters 2 and 3 are considered together to provide an overall view of the global pattern of technology identified thus

far. The technology difference identified using the Cobb-Douglas specification persists in the translog, even though Table 3.7 rejects the Cobb-Douglas restriction. This is evidence that the first order approximation of the Cobb-Douglas was not falsely identifying difference. Although the interaction terms are jointly significant, the Cobb-Douglas is still useful as it is easier to interpret and can succinctly present some of the salient features. We can turn to the translog where it provides useful extra information, for example, about factor substitution. Doing this we see that there is a technological difference between firms in these country groupings, and that this is not the result of scale or secular coefficient evolution over time. There is evidence in Tanzania that, within a common translog technology, larger firms use inputs in a different way to smaller firms. We were unable to find evidence of a common translog technology across all countries, and so technological switching would appear to be part of the development story. Firms use different technologies but are not engaged in a transition along an expansion path over time or scale. Given that they use different technologies which are correlated somehow with income per capita, this is highly suggestive of technological switches being an important part of the development process.

This quantitative investigation of technology across six countries has led to a consistent picture of technology. Broadly, we see an intercept/TFP term that does not differ significantly between countries. Output elasticities, i.e. the β s, and the return on education differ systematically by levels of income per capita. The evidence presented here is suggestive of the output elasticities and the return on education being jointly determined. Using material intensity as an index of technological sophistication, we have seen

that the most material intensive technology is that of Tanzania, followed by GKN, South Africa and, finally, South Korea. The estimates of the return to education in each of these countries are also consistent with the rate rising as the share of materials falls. No country in our sample is observed for a sufficiently long period for a technology switch to be observed in the data, but the fact that the ordering of technological sophistication is identical to the order of GDP per capita is highly suggestive that the two are associated.

As part of the transition from a low-skill economy, such as Ghana's, to a high-skill economy, such as South Korea's, it appears that the technology used by firms needs to change. The way in which production is organised and inputs are used will require different sorts of firms to be formed in Ghana if the economy is to make this transition. It follows that we need to understand the process by which firms make choices about their production structure, how this may be influenced and the possible consequences of adopting different technologies. Given that manufacturing is a globalised industry, so intellectual property is widely available, and that foreign firms are more-or-less free to set up in Africa, the most likely scenario is that African firms are using a different technology because they choose to do so. If one technology produces more output than another for all levels of inputs, then clearly a rational unconstrained firm will always choose to use it. The more interesting case, and consistent with the previous quantitative investigation, is where technologies cannot be unambiguously ranked over all relevant input bundles.

Recall Table 2.2, which shows that technology and the return to education differ substantially between Ghana and South Korea and can account for the

entire difference in output per worker. The major quantitative differences between the production functions of the two countries are that the material elasticity of output is much higher for Ghana, the labour elasticity is much lower, and the rate of return on education is lower and convex. Can we ask: will a firm ever prefer to use the Ghanaian technology?

If two production functions differed only in the level of total factor productivity then the function with higher TFP would clearly be preferable: for every combination of inputs, it will produce more output. However TFP does not differ significantly between the countries in our sample. The only country for which it is not possible to reject the hypothesis of common TFP terms in the production function was South Africa. South Africa was also the only country for which we do not have data on the education of the workers. Furthermore, the rate of return required to remove the apparent TFP difference is consistent with South Africa's position in the technological hierarchy.

Consider now South Korea and Ghana. Even for firms producing similar levels of output, South Korean firms produce more output per worker than Ghanaian firms. This is due to factor ratios rather than TFP. The unit cost of labour is much lower in Ghana and so, while TFP is not significantly different, output per worker is lower as Ghanaian firms will rationally use more of the cheaper input. Despite the lower level of output per worker, Ghanaian firms may not prefer to use the South Korean technology. Ghanaian firms have fifteen times less capital per worker but only ten times less material input per worker. Even aside from scale, Ghanaian firms use capital relatively less intensively than South Korean firms. If this is because the shadow price of

capital is relatively high in Ghana, then using the South Korean technology may result in lower levels of expected profit.

In this section we build a theoretical framework that uses the way in which technology differs to understand why it may differ. The idea is that firms use production techniques with varying intensities of variable factors due to differential effects of risk.

3.5.1 Technology Across Countries

There are a number of theoretical and empirical justifications for technological heterogeneity. Jones [2005] puts forward the idea that the standard production function that is written can be viewed not as a single production function, but rather as a representation of the substitution possibilities across a range of technologies. Caselli and Coleman [2006] show that skilled and unskilled workers are used in different ways across countries and hypothesise that countries are choosing technologies best suited to their endowments. Elberfeld and Götz [2002] show that different technologies can persist due to differences in market size. Deardorff [2001] develops a model in which diverse endowments lead to distinct specialization cones with a common technology: despite having the same menu of choices open to them, countries will end up producing differently. Other models have technological differences as an important element [Grossman and Helpman, 1995]; however, take differing technologies as exogenous, perhaps due to uninsurable chance events or differences in ex ante opportunity costs.

Why might technology differ? Perhaps it is through constraint, such as

access to intellectual property or credit. But in an increasingly global market for manufactures and the firms that produce them, this argument is more difficult to sustain. In this case why, for example, would South Korean firms not buy their Ghanaian counterparts and bring in the new technology? This leads to the idea that firms in Ghana are choosing, for whatever reason, to use a different technology to those in South Korea.

Consider a ‘small’ technology with low fixed costs and high variable costs and a ‘large’ technology with high fixed costs and low marginal costs. Assume that firms are engaged in Cournot competition and that switching between the technologies involves a fixed cost. Investing in a new technology could be considered akin to capacity choices or investments to reduce marginal costs. A separating equilibrium can be sustained even in a symmetric model with risk-neutrality as long as the difference in marginal costs is below a certain threshold. A firm will be more likely to switch to the larger technology the greater the market size, the more significant the cost advantage and the lower the switching cost.¹⁰ The model can be enriched by allowing profits (potentially expressed in certainty equivalents) under each technology to differ by country of the firm - thereby providing a way to allow the ex ante distribution of profits and risk preferences to differ between countries.

This framework encapsulates a number of relevant factors which provide further theoretical support: market size (through total quantity), network externalities (the numbers of firms using each technology), switching costs, irreversibilities and risk (the profile of the risk-adjusted profit distribution).

¹⁰These results, although intuitive, can formally be derived from a Cournot model with two firms, two technologies, a switching cost and linear demand.

Market size may have an impact, not only through the scope for spreading fixed costs over a larger number of units, but through its effects on the cost of adoption. It is well known that the cumulative distribution function of adoptions over time is S-shaped; that is, imitation is initially slow, then accelerates until eventually slowing down as saturation is reached. This suggests that there may be some network externalities in the adoption of new technology and it is why we consider technology choice at the country level.

3.5.2 Materials and Risk

There is a large literature taking the view that, directly or indirectly, risk and uncertainty are key to understanding the poor performance of African economies [Bleaney, 1996, Servén, 1997, Ibarra, 1995]. Uncertainty can lead to firms being less willing to commit to sunk costs [Lambson, 1991]; however, the effect of risk on investment is ambiguous and firms may end up with excess capital stocks in a risky environment [Abel and Eberly, 1999]. Adoption of the large technology in a developing country is possibly deterred by poor resale value of equipment, with the irreversibility decreasing as the penetration of the large technology increases, thus creating an externality. Pack [1993] notes that African markets are not filled with potential entrants to buy physical assets of defunct firms, so when bankruptcy occurs, it generally results in dispersion of skilled workers and loss of productive power of physical equipment, rather than their transfer to a more productive firm.

Table 2.2 tells us that materials are important, and we specifically propose that the *ex ante* distribution of discounted expected profits for Ghanaian

firms differs in such a way so as to make them prefer material intensive production, perhaps due to credit constraints [Bigsten et al., 2003, Habyarimana, 2003], lack of outside options for firm owners and managers, or market size. Firms substitute away from fixed investments in human and physical capital and into materials so as to minimise their exposure to downside risk. What economic intuition can support the idea that a small technology will provide some insulation from shocks? Consider the following scenario. When a firm using the large technology receives a positive demand shock, it is able to easily expand output and increase profit. However, when it receives a negative demand shock, it cannot reduce costs optimally due to its capacity commitment and so suffers a period of loss. Conversely, a firm using the small technology is able to respond to both shocks, but cannot increase production beyond a relatively low capacity constraint. That is, they cannot gain substantially from any upside, but limit their downside risk. Thus, for a given demand shock distribution, the resultant shocks to firm profit have a lower variance if using the small technology.

Given that so many authors implicitly assume that materials are separable from capital and labour inputs, is it possible to develop some intuition as to how materials may interact with these inputs? Materials may be substitutable with labour and skills. Workers in a textile firm with more employees will be able to be more specialized and hence reduce wastage from production errors. More highly skilled workers may also be able to use materials in a more efficient way, such as through managing stocks at a bakery to reduce losses through perishable ingredients spoiling, in the same way that they may operate and maintain machinery more effectively.

Significant capital-material substitution has been empirically found, for example, by Campbell and Jennings [1990], in an econometric study of the Tasmanian sawmilling industry. In this context it is easy to imagine purchasing machinery that allows for raw logs to be sawn in such a way so as to obtain more planks. Output could then be maintained with a reduced level of material inputs. A similar argument can be applied to many manufacturing firms. For example, a garment firm may have the option to purchase a more sophisticated piece of equipment that can cut and sew with greater accuracy thereby allowing more shirts to be cut out of a given length of cloth. Another innovation that would result in capital-material substitution is that of just-in-time inventory systems. Excess supplies of raw materials represent a cost to the firm, such as through storage costs and cash-flow restrictions, and so they will generally wish to minimise stocks. However, the risk of running out of a key material due to poor inventory management will induce firms to hold a buffer of materials. Investment in inventory management systems (capital) that enable more effective management of inventories will allow firms to reduce their inputs of materials due to the investment. Fafchamps, Gunning and Oostendorp [2000] show that Zimbabwean firms respond to risk by increasing their inventories, which is another example of how risk results in conservative and possibly costly behavior in material and indirect input use. We now formalise these ideas in a simple model.

Theorem 3.5.1 *Assume that all firms are risk-neutral, maximise discounted expected profits, have a constant discount factor δ and are subject to serially uncorrelated profit shocks σ with mean 1, a symmetric distribution and a*

cumulative density function $F(\sigma)$. Further, assume that South Korean firms are infinitely lived, but Ghanaian firms will cease to exist if they receive a negative shock of magnitude larger than σ^* . If a firm uses the small technology there is a mean-preserving transformation of the impact of the shock such that the cumulative density function of the shock changes to $G(\sigma)$. Ghanaian firms will endogenously choose the small technology if $G(\sigma^*) < F(\sigma^*)$.

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

$$V_t = E(\Pi_t) + \delta V_{t+1} \quad (3.5)$$

$$= \Pi^0 E(\sigma) + \delta V_{t+1} \quad (3.6)$$

$$= \frac{\Pi^0}{1 - \delta}. \quad (3.7)$$

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

$$V_t = E(\Pi_t) + \delta V_{t+1} \quad (3.8)$$

$$= \Pi^0 E(\sigma) + \delta E(I_{\sigma > \sigma^*} V_{t+1}) \quad (3.9)$$

$$= \Pi^0 + \delta(1 - F(\sigma^*))E(V_{t+1}) \quad (3.10)$$

$$= \Pi_{i=0}^{\infty} [\delta(1 - F(\sigma^*))]^i \Pi^0. \quad (3.11)$$

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

$$V_t = E(\Pi_t) + \delta V_{t+1} \quad (3.12)$$

$$= \Pi_{i=0}^{\infty} [\delta(1 - G(\sigma^*))]^i \Pi^0. \quad (3.13)$$

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

Example 3.5.2 Let $F(\sigma)$ be uniformly distributed over the interval $[0, 2]$ and $G(\sigma)$ be uniformly distributed over the interval $[1 - \epsilon, 1 + \epsilon]$. Ghanaian firms will endogenously choose the small technology if $\epsilon < 1$.

The key assumption is the $F \rightarrow G$ transformation: Ghanaian firms are more affected by negative shocks. Many of the assumptions in the model could be relaxed without affecting the fundamentals of the result. Allowing δ to differ between countries has no impact upon the results. Similarly, if the distribution of the shocks is constant over time, a time-varying discount factor will not change the result. Again, because the result hinges upon a within-country choice, the distribution of the shocks could be allowed to vary over time with a time-varying discount rate so long as F and G were transformed in the same way. The distribution of the shock can also differ between countries as long as the transformation is still mean-preserving.¹¹ If the F and G distributions vary over time and the discount rate is time-varying, then it would not be possible to determine a technology choice condition without specifying how each parameter evolved. The risk-preferences of the

¹¹The separating equilibrium can still persist if the transformation is not mean-preserving, but then only under a narrower range of conditions.

firms could also be easily generalised, most simply by using a risk-weighted measure of profit. If a firm is risk-averse then it will place more weight on the probabilities of going bankrupt and so will be more likely to choose the technology that reduced its likelihood of ceasing to exist. This can also be modelled as a decrease in the discount factor (an increase in the discount rate). Finally, profits could also differ between technologies within a country - this would merely change the form of the switching condition.

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

any ambiguity from South Korean firms being indifferent between the two technologies.

3.6 Concluding Remarks

African technology is relatively more intensive in its use of variable inputs and less intensive in its use of fixed factors. Moreover, we have seen that the variable factors (loosely, I and M) are substitutable with other inputs, consistent with the idea that a material-intensive technology is more flexible and can insulate the firm from shocks. The ways in which the fastest growing country in this sample, Tanzania, differs from the others is also instructive. In Tanzania technology changes with size and larger firms use inputs in a different way to smaller firms. In a Cobb-Douglas framework this would exhibit itself as TFP increasing in firm size and we have been able to identify the source of this apparent productivity difference. The use of intermediate inputs has also been decreasing over time, providing evidence that input use is correlated with development. Neither of these effects were observed in firms in the other countries. In addition the technological differences across countries are also observed when the analysis is restricted to a single manufacturing sub-sector.

We have established a link between technology choice and development, but we have not shown causation in one direction or the other. It seems reasonable to expect that they are somewhat jointly determined, influenced by what is termed the general ‘investment climate’. That Tanzania has grown so rapidly in this period suggests that development can occur without

a technological shift; however, we never observe a country using a smaller technology with a higher level of per capita income than a country using a larger technology. We can imagine that, as an economy grows, at some point firms will want to switch. For example: as better access to credit reduces insolvency risk and so makes the larger technology more attractive; as factor prices adjust (e.g. farm wages rise and so firms want to get a higher marginal product out of workers, or political stability makes the cost of capital fall); or, as the quality of education improves to the point where there are sufficient skilled workers to exploit the larger technologies.

The production functions in Tables 2.2 and 3.2 are consistent with the world technology frontier presented in Equation 3.1. Not only does technology differ by stage of development, but it does so in a very specific way which we have been able to characterise quantitatively. Countries with lower levels of GDP per capita use a manufacturing technology in which the output elasticity of labour is lower, that of materials is higher, and in which the firm return to worker education is low. Rising incomes are associated with an increased return 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 thesis, 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 payments to the owners of capital. An important element of the process of development is the technological shift whereby production uses intermediate inputs less intensively.

As part of the transition from a low-skill economy such as Ghana's to a high-skill economy such as South Korea's it appears that the technology used by firms needs to change. The way in which production is organised and inputs are used will require different sorts of firms to be formed in Ghana if the economy is to make this transition.

Chapters 2 and 3 have demonstrated the importance of technology for explaining the sources of microeconomic productivity differentials across countries. In turn, the way in which firms use skills has been shown to be an important element of technological heterogeneity. In Chapter 4 the issue of skills is probed in more detail. By simultaneously comparing the effects of observable and unobservable human capital on worker earnings and firm productivity we will be able to understand the effects of education identified in Chapters 2 and 3 in terms of externalities, unobservable human capital, selection effects and worker productivity.

3.A Elasticities of Substitution

The calculation of substitution elasticities is a non-trivial matter. There are a plethora of possible definitions in the literature and no consensus on which are most accurate [Stern, 2004, Behar, 2007, Blackorby and Russell, 1981, Blackorby and Russell, 1989]. In fact, if anything, the current consensus would be that there is no such thing as “the” elasticity of substitution. See Behar [2007] for a comprehensive discussion. There are two main concepts of the elasticity of substitution: one developed by Allen [1967] and Uzawa [1962], and a second due to Hicks [1970].

Allen [pp.340-3] stated that, in a two-factor model with constant output and a given change in input quantities, the elasticity of substitution is defined as the ratio of the proportionate change in the ratio of input quantities to the proportionate change in the marginal rate of substitution (MRS). Mathematically this can be represented as:

$$\sigma_{ij} = \frac{\frac{q_i}{q_j} d\left(\frac{q_j}{q_i}\right)}{\frac{dq_i}{dq_j} d\left(\frac{dq_j}{dq_i}\right)} = \frac{d \ln \left(\frac{q_j}{q_i}\right)}{d \ln \left(\frac{dq_j}{dq_i}\right)}. \quad (3.14)$$

If $\sigma_{ij} < 0$ then inputs i and j are complements in production, and substitutes if $\sigma_{ij} > 0$.

For the two-input case, the specification presented in Equation 3.14 has a clear meaning, as the definition of the MRS is precise in two-dimensional space. In contrast the curvature in n -dimensional space is dependent upon the direction in which it is measured. In order to unambiguously generalise to the n -factor case, it is necessary to specify the direction in which the MRS is measured. The Allen elasticity of substitution (AES) imposes such a restriction by assuming, in addition to constant output, that all input quantities other than of i and j remain fixed. This generalisation can be defined in terms of the cost function, C :

$$\sigma_{ij} = \frac{CC_{ij}}{C_i C_j}. \quad (3.15)$$

In this definition of the elasticity of substitution, output and the price of all other factors are constant. Note, this has the implication that it is a net measure. The Allen extension to the n -factor case is merely formal, with the

expectation that changes in the input quantities of i and j will have no impact upon the quantities demanded of other inputs. Furthermore $\sigma_{ij}^A = \sigma_{ji}^A$: the AES is symmetric. Blackorby and Russell [1989] argue that, because partial differentiation requires that only the i th price in the ratio $\frac{p_i}{p_j}$ vary, symmetry is not a natural property of n-factor elasticities of substitution. Allowing p_j as well as p_i to vary would entail variation in all other price ratios, contrary to the definition of partial differentiation.

Hicks' definition is defined in terms of the production function f as:

$$H_{ij} = \frac{f f_{ij}}{f_i f_j}. \quad (3.16)$$

In this definition the output price and the quantity of the other factors are fixed with the implication that it is a measure of gross substitution. It measures the percentage change in the relative marginal products after changes in the relative quantity of other factors used in production. Assuming positivity of the production function and its first derivatives, the sign of this expression will be the same as that of the second derivative. There is an apparent obvious symmetry between the Allen and Hicks definitions and, in the two factor case, one is the inverse of the other. Unfortunately this simple relationship does not hold in the multifactor case.

Blackorby and Russell [1981, 1989] have argued that the correct definition of the multi-factor elasticity of substitution is the Morishima elasticity of substitution - a variant of the Allen-Uzawa concept. Morishima's intuitive definition was that, for a given change in $\frac{q_i}{q_j}$, σ_{ij} is defined as the ratio of the proportionate change in $\frac{q_i}{q_j}$ to the proportionate change in the MRS after

all the input factors have adjusted, measured in the direction such that all other MRS remain unchanged.¹² Measuring in the direction such that all the other MRS remain unchanged is the constraint that allows the direction of measurement to be precisely defined.

A translog production function does not necessarily imply a translog cost function [Beattie and Taylor, 1985]. Thus it may be that a homothetic production function has a cost dual that is not homothetic; for example, if factor prices differed systematically by firm size. The major relevance of this point is the implication for the calculation of elasticities, as such calculations are based upon the output derived from one function or the other. Elasticities calculated from a cost function will not, in general, be equal to those calculated through the use of a production function. Humphrey and Moroney [1975] find that those elasticities calculated from a cost function, in general, are lower than those calculated from employing a production function.

The complexities of multi-factor environments, differing exogeneity assumptions and the need to impose further non-trivial restrictions means that it is impossible to arrive at a definition of “the” elasticity of substitution. For a production function the exogeneity assumptions make the Allen-Uzawa style concept not applicable. Under the Hicks definition, often referred to as the elasticity of complementarity, two inputs are said to be q-substitutes if $H_{ij} < 0$ and q-complements if $H_{ij} > 0$. In order to avoid the complexities of calculating a number for the elasticity of substitution this analysis will consider the signs of the second-derivatives alone as a proxy for the sign of

¹²Note that the constant output restriction remains.

H_{ij} .

Properties of the production function may differ for different input ranges. To allow for endogenous technological change, an elasticity measure that allows for such differences, if present, to exhibit themselves is required. Firstly, output elasticities are calculated. These are simply the first derivative of the production function and so are simple to calculate and allow for differentials across input ranges. The output elasticities also allow an indirect comparison with the Cobb-Douglas coefficients.¹³ Secondly, any measure of substitution between inputs will be dependent upon the cross-derivative of output with respect to the two inputs, which, in the translog framework, will be the coefficient on the interaction term c_{ij} . Comparing the signs of the cross-derivatives will indicate how the marginal productivity of one input is affected by changes in the input level of another. For example, if this coefficient was positive, it would be evidence to suggest that the inputs are complements. An increase in the level of input i would then increase the marginal productivity of input j which, in turn, would *a priori* cause the optimising firm to increase the level of input j . This second indicator of the elasticity properties is of course not dependent upon input levels but does provide an intuitive reason as to why consideration of the second derivative is an appropriate way to consider substitution possibilities.

¹³Using a Cobb-Douglas function, the input coefficients are equal to the output elasticities and so calculation of the latter from the translog gives a simple way to interpret the implications of the set of first and second-order translog coefficients which do not have such a simple direct interpretation.

Chapter 4

Skills and Human Capital in Earnings and Production Functions

In this chapter we seek to identify possible sources of the low return to schooling in Ghana and compare the return implied by both earnings and production functions. Skills are modelled by allowing for both unskilled and skilled labour, defined in terms of occupations, to enter the production function. Such a specification relaxes the assumption, implicit in the specification of previous chapters, that different levels of education are perfect substitutes. We test for imperfect substitution between skilled and unskilled labour and find that the Cobb-Douglas specification cannot be rejected. We also test for a role of education in enhancing the firm return to education conditional upon worker occupation and find no evidence of such an effect.

Earnings functions are estimated, for both skilled and unskilled labour,

both with and without an extensive set of firm level controls in order to ascertain whether returns are sensitive to firm characteristics. The importance of education for selection into occupations is modelled explicitly, allowing us to identify if there is an impact of education upon earnings beyond selection into occupations. Possible endogeneity of education in the earnings function is investigated using both an instrumental variables and a Heckman selection approach. The conditional earnings premium for skilled workers is 50% for those with up to ten years of education and increases by 10% for each additional year of schooling obtained beyond this. Unskilled workers receive a virtually zero return to schooling. Selection into jobs and firms is an important determinant of earnings and schooling is mostly useful insofar as it assists with this selection.

The finding that the individual return to education is only high for relatively educated skilled workers is open to the interpretation that such labour is complementary with more sophisticated technology thus providing an explanation as to why the return to education is so low in Ghana where technology lacks sophistication for most firms.

4.1 Introduction

In this chapter we seek to understand why the return to education is so low in Ghana and to identify more precisely the role of schooling by recognising that human capital has many dimensions and that these may affect estimates and understanding of this return. Technological differences can explain almost all of the observed gap in output per worker between firms in Ghana and those

in South Korea, and we have seen in Chapter 2 that the return to education is particularly important. To understand these differences we need to look at the impact of education on the individual in the context of the production structure. In this chapter we will extend earlier models of production and also introduce the earnings function to understand the role of education. Skilled and unskilled labour will be differentiated based upon occupation in recognition of the fact that education can have selection and productivity effects and because it may have a different return to workers and firms across occupations. A variety of econometric techniques to address endogeneity, potentially caused by unobserved ability, and an extensive set of control variables will be exploited to determine if estimates of the return to education are sensitive to this broader view of human capital.

We propose to relax the assumption underlying the production function in Chapter 2 that education acts simply as a shifter of the underlying TFP. Chapter 3 used education to augment the measure of labour input and a further alternative specification is pursued in this Chapter. Skilled and unskilled workers will be differentiated and the technology, as embodied by the production function, will allow for imperfect substitutability between workers of different skill types. So far in the literature there have been two approaches to including skilled labour in the technology. The first is the approach of Hall and Jones [1999] where years of education acts as a shifter, while the second is that adopted by Caselli and Coleman [2006] where labour input is a CES function of skilled and unskilled labour. We use a more general CES framework in this chapter to consider these questions, and allow the return to education to differ between skilled and unskilled workers. Identifying the

return to education conditional on workforce composition is important as we wish to know whether the low average return in Ghana is the result of workforce composition (e.g. a low proportion of skilled workers in Ghana as opposed to South Korea).

In the early history of studying earnings in Africa the possibility that education acted as a signal or that educational qualifications acted as a sorting mechanism were extensively investigated. The general finding of this literature was that education was important because of its impacts upon human capital, rather than as a signal or a credential. Boissiere et al. [1985] showed that direct measures of human capital, ie the skills workers possessed, were created by education and impacted upon earnings. Once the impact of education on measurable skills was taken into account, years of schooling had only a moderate effect of earnings. This suggests a productivity role for education. However, later, Knight et al. [1992] investigated the impact of the rapid expansion of education in Africa on the return and found that it differed considerably over time. In particular, there was evidence that the expansion of education had not kept pace with formal job creation; leading to educated workers filtering down into lesser occupations as education expanded. This suggests a sorting role for education; where the return falls as education becomes more widespread. Thus the early literature using earnings functions in Africa leaves a potential role both for a productivity and a sorting effect of education. The emergence of matched firm and labour market data enabled the analysis to be extended to a comparison across earnings and production functions. Bigsten et al. [2000] found that the return on physical capital greatly exceeded that on human capital and that, across a range of African

countries, there was strong evidence for the convexity of the earnings function. These findings mirror those of Chapter 2 where a contrast was found between the convex return in Ghana and the concave return in South Korea, and technological heterogeneity was identified as a crucial element of output per worker differentials.

In this chapter we investigate the robustness of the result of a convex return to education in Africa, and related elements of the structure of the labour market. A concave return to education is routinely assumed [Card, 2001, Hall and Jones, 1999], and is *a priori* appealing; however, the evidence of Chapters 2 and 3, and others [Knight et al., 1992, Bigsten et al., 2000], is indicative that this may not be appropriate for Africa. If there is convexity in the return to education, many standard models of the choice of education will not be applicable. Serious policy questions would also arise out of a finding that there is a very low return to compulsory education as this is all many workers receive.

Earnings functions are estimated separately for skilled and unskilled workers so that the overall impact of education on wages can be separated into an effect due to selection into occupations and a productivity effect conditional upon occupation. We use a probit model to estimate the effect of education on selection into a skilled occupation, where education is permitted to be potentially correlated with unobservable factors that also influence selection. These models identify the selection effect of education. This can be combined with estimates of the earnings premium from an extra year of education conditional upon occupation to gauge the unconditional impact of education on earnings. This separation is necessary to allow the identification of the

aspect of the return to education that can be linked to the production function. Education will impact on the production function to the extent that the marginal product of workers increase as a result of education, but not to the extent it sorts workers between occupations. Skilled workers have higher wages than unskilled workers and, if skilled workers differ in some unobservable characteristics or experience a different return to schooling, estimating a pooled earnings function will result in estimates that would not reflect the corresponding productivity effect of education in production.

As with production functions, endogeneity is a concern in the estimation of earnings functions due to the possibility that unobserved factors that influence earnings may be correlated with education. If these unobserved factors are captured by the occupation of the worker then this problem may be mitigated. Nonetheless, instrumental variables are used in both two-stage least squares and Heckman selection equations to allow for the possible endogeneity of education. Finally, the earnings functions are estimated both with and without an extensive set of firm and worker controls to test how sensitive the estimates of the return are.

In the next section we outline the models that will be used in the empirical investigation. Section 4.3 describes the data used for the investigations in this chapter. Section 4.4 begins the analysis at the firm level; differentiating between skilled and unskilled workers in the production function and introducing the CES functional form to allow a more general analysis of the role of skills and education in firm productivity. In Section 4.5 we turn to the level of the individual and investigate the impact of education upon earnings and occupation; enabling us to comment upon the return to education, the

extent of education as a sorting mechanism, skill premia and the link between technology and human capital. The return to education experienced by firms and workers is compared in Section 4.6. A final section concludes the chapter.

4.2 Modelling Skills and Human Capital

Two main approaches have been used to incorporate skills into the production function. The first is the approach of Hall and Jones [1999], where skills are equated with years of schooling and act as a TFP shifter:

$$Y_{it} = K_{it}^{\alpha} (A_{it} e^{\phi(E_{it})} L_{it})^{1-\alpha} e^{u_{it}}. \quad (4.1)$$

This is analogous to the approach embodied in Equations 2.1 and 2.2. In Equation 4.1, an increase in the number of years of schooling will have a multiplicative effect on value added, or an additive effect in logs. Also implicit in this approach is the assumption of perfect substitutability between workers of different skill levels. Caselli and Coleman [2006] relax this assumption of perfect substitutability and use a production function of the form:

$$Y_{it} = K_{it}^{\alpha} [(A_u L_u)^{\sigma} + (A_s L_s)^{\sigma}]^{(1-\alpha)/\sigma}. \quad (4.2)$$

The labour input into production is a CES aggregate of the number of skilled and unskilled workers. The parameters A_s and A_u are analogous to the TFP term A in Equation 4.1 and represent the relative efficiency with which skilled and unskilled workers are used. Caselli and Coleman's definition of skills is

again related to schooling; with workers being classified as skilled if they complete Primary School, and unskilled otherwise.

An innovation in this chapter is to include skills in the production function in a more general way. In particular, our data enables us to use both schooling and occupation as related elements of human capital. In the most general case, we will consider labour input as an aggregate of the number of skilled and unskilled workers (with the classification based upon occupation) and of their respective average number of years of schooling. As well as considering the impact of schooling on occupation, we are able to determine if, within a skill category, workers are heterogenous in a way which is systematically related to schooling. Further, as in Chapters 2 and 3, we also frame the production function in terms of gross output rather than value added.

We wish to allow for imperfect substitution between skilled and unskilled labour; however, for tractability, we need to place some restrictions on the substitution possibilities. This is done by considering only functional forms where the elasticity of substitution between components within the labour aggregate is constant. In the multi-input case the correct measure of elasticity of substitution between an input pair is ambiguous: the proportionate change in the MRS between two inputs is not unique and so additional conditions need to be imposed. The Morishima Elasticity of Substitution (MES) measures the elasticity of substitution between two inputs as the proportionate change in the MRS between the two inputs after all the input factors have adjusted, keeping each MRS applying to other input pairs unchanged. The Allen Elasticity of Substitution (AES) definition uses, instead of this

latter condition, the restriction that all other input quantities remain fixed.¹ Blackorby and Russell [1989] argue that the MES is preferable over the more common AES. Moreover, in the multi-input generalisation of the CES production function, it is in fact the MES that is constant across all input ranges, rather than the AES. Blackorby and Russell [1989] show that the MES are constant if and only if:

$$Y = [a_1x_1^\rho + \dots + a_nx_n^\rho]^{1/\rho}; \quad (4.3)$$

$$0 \neq \rho \leq 1, a_i > 0 \forall i, \sum a_i = 1.$$

Paraphrasing Blackorby and Russell, if Equation 4.3 is ‘the’ CES production function, then the MES is ‘the’ elasticity of substitution. Hence the estimates of the parameter ρ which follow should be interpreted as MESs.

The Cobb-Douglas is the limiting case of Equation 4.3 where $\rho \rightarrow 0$. Here ρ is a substitution parameter related to σ , the elasticity of substitution between skilled and unskilled labour. The relationship can be derived from the definition of the two-factor elasticity of substitution: the percentage change in the factor ratio divided by the percentage change in the technical rate of substitution (TRS) with output held constant, where the TRS is the slope of the isoquant [Varian, 1992]. In natural logarithms and defining

¹See Appendix 3.A for a discussion on the distinction between the MES and the AES.

$y = [a_s L_s^\rho + a_u L_u^\rho]^{\frac{\beta_L}{\rho}}$, we have:

$$TRS = \frac{\partial L_s}{\partial L_u} \quad (4.4)$$

$$= -\frac{\partial y / \partial L_u}{\partial y / \partial L_s} \quad (4.5)$$

$$= -\frac{a_u}{a_s} \left(\frac{L_u}{L_s} \right)^{\rho-1}. \quad (4.6)$$

$$\text{So, } \ln \frac{L_s}{L_u} = \frac{1}{1-\rho} (\ln |TRS| - \ln(a_u/a_s)). \quad (4.7)$$

$$\text{Now, } \sigma = \frac{d \ln(L_s/L_u)}{d \ln |TRS|} \quad (4.8)$$

$$= \frac{1}{1-\rho}. \quad (4.9)$$

Note that if $\sigma = 1$ then this reduces to the Cobb-Douglas form.

For simplicity, and as we have already used the translog production function to investigate substitution possibilities between the input set (K, L, I, M) , we retain Cobb-Douglas substitution between these four aggregates and focus on substitution within the labour input. Considering the labour aggregate as composed of workers of two skill types (skilled and unskilled) and years of schooling, the most generalised form of the labour aggregate within our framework is a double-nested CES function (firm subscripts omitted):

$$L = ((bS^{\rho_s} + (1-b)E_s^{\rho_s})^{\rho/\rho_s} + (cU^{\rho_u} + (1-c)E_u^{\rho_u})^{\rho/\rho_u})^{1/\rho}; \quad (4.10)$$

where S is the number of skilled workers, U is the number of unskilled workers, E_s is the average number of years of schooling of skilled workers, and E_u is the average number of years of schooling of unskilled workers. Equation 4.10 parameterises the labour aggregate as a CES function of skilled and unskilled

labour, where the two skill types are in turn each considered to be a CES function of the number of workers and their education. Skilled labour input, $(bS^{\rho_s} + (1 - b)E_s^{\rho_s})^{1/\rho_s}$, and unskilled labour input, $(cU^{\rho_u} + (1 - c)E_u^{\rho_u})^{1/\rho_u}$, are aggregated into total labour input with a CES parameter of ρ . In turn, skilled labour input is a CES aggregate of the number of skilled workers, S , and their average number of years of schooling, E_s , with substitution parameter ρ_s and relative efficiencies b and $(1 - b)$. A similar relationship holds for unskilled labour input and the parameters ρ_u and c . Equation 4.10 has the advantage of imposing few restrictions on the form of the labour aggregate but the disadvantage that it achieves identification only through its non-linearity. Identification through functional form is not ideal and so a number of special cases are considered which do not achieve identification in this way.

Equation 4.2, as used by Caselli and Coleman [2006], is the special case of Equation 4.10 where $b = c = 1$ (in which case ρ_s and ρ_u drop out). This restriction implies that, conditioning on occupation, education has no effect on output. In our Equation 4.10 we allow for worker heterogeneity (as a function of schooling) even when they are in the same skill category. The restriction implied in the Caselli and Coleman version is estimated and tested for; although, for consistency with Equation 4.10, it is parameterised slightly differently as:

$$L = (aS^\rho + (1 - a)U^\rho)^{1/\rho}. \quad (4.11)$$

An alternative restriction that could be imposed in Equation 4.10 is making the skilled labour sub-aggregate a Cobb-Douglas function of the number

of skilled workers and their education, rather than a CES function, and similarly for unskilled labour. With this restriction, $\rho_s = \rho_u = 0$ and the labour aggregate collapses to:

$$L = (aS^{\rho_s} E_s^{\rho(1-\rho_s)} + (1-a)U^{\rho_u} E_u^{\rho(1-\rho_u)})^{1/\rho}. \quad (4.12)$$

If $\rho_s = \rho_u = 0.5$ then Equation 4.12 would be similar to the approach of Chapter 3 where labour input was measured as number of workers multiplied by years of education.

The Hall and Jones [1999] Equation 4.1 is a further specialization where $\rho = 0$ which, in the limit, leads to the pure Cobb-Douglas specification. Through the estimation of Equation 4.10 we can test for the specifications of Equations 4.1, 4.11 and 4.12; that is, whether labour is homogenous (with respect to schooling) within skill categories, and the form in which education enters the production function.

Omitting firm and year subscripts, we thus take as our estimation equation the nested Cobb-Douglas/CES production function:

$$Y = AK^{\beta_K} [L]^{\beta_L} I^{\beta_I} M^{\beta_M} e^{xX}. \quad (4.13)$$

Unless otherwise mentioned, all variables have their usual meaning and X represents a vector of firm characteristics. $[L]$ is the labour aggregate, given in the most general form by Equation 4.10. Equation 4.13 is estimated in logs using non-linear least squares. The nested labour aggregation function exhibits constant returns to scale by construction; however, the production

function is not necessarily constant returns to scale in the four aggregate inputs and the test is, as usual, $\sum_{i=K,L,I,M} \beta_i = 1$.

The estimation strategy will begin with Equation 4.13 and the generalised labour nest given by Equation 4.10. There are then two approaches we can take to simplify the equation. The first is to test $b = c = 1$ in which case the production function collapses to Equation 4.11. Alternatively, we could test $\rho_s = \rho_u = 0$ in which case the skilled and unskilled labour aggregates become Cobb-Douglas, rather than CES, aggregates of the number of workers and their schooling as in Equation 4.12. We also test for CRS in the aggregate inputs in the usual manner.

In the event that we cannot reject the null $\rho = 0$, the production function could be collapsed to a pure Cobb-Douglas in up to seven inputs:

$$Y_{it} = AK_{it}^{\beta_K} S_{it}^{\beta_S} E_{s,it}^{\beta_{Es}} U_{it}^{\beta_U} E_{u,it}^{\beta_{Eu}} I_{it}^{\beta_I} M_{it}^{\beta_M} e^{xX}. \quad (4.14)$$

However, note that this would imply a $\ln E$ term in a Mincerian earnings function, i.e. a necessarily concave return. A logarithmic specification of education within a production function is inconsistent with the micro evidence supporting the Mincer model, and can result in insignificant and wrongly signed estimates [Topel, 1999, Krueger and Lindahl, 2001]. As we wish to allow for the return to education to be convex we take the more general approach of including education as (dropping subscripts):

$$Y = AK^{\beta_K} S^{\beta_S} U^{\beta_U} I^{\beta_I} M^{\beta_M} e^{xX} e^{\delta_{s1}E_s + \delta_{s2}E_s^2 + \delta_{u1}E_u + \delta_{u2}E_u^2}. \quad (4.15)$$

In the event that the logarithmic specification is correct, we will observe a strictly increasing concave quadratic (over the relevant range) approximating a logarithmic function in the earnings equation. Krueger and Lindahl [2001] also note the importance of allowing for quadratic effects of education on output and find that a linear effect is rejected by the data.

For South Korea, it is not possible to undertake an approach as general as the one embodied in Equation 4.10 as we only have education at the firm level for the South Korean firms, and there is no information on the relative years of schooling acquired by workers of different occupations. Thus the scope for comparative analysis is limited. The baseline for a South Korean CES is just to have the standard 2-factor CES nest in numbers of skilled and unskilled workers for $[L]$, and including average firm level education as a separate input. The form of $[L]$ used in Equation 4.13 for South Korea is given in Equation 4.16:

$$[L] = [aS^\rho + (1 - a)U^\rho]^{1/\rho}. \quad (4.16)$$

As there is no observable variation between skill types in education any difference can only be identified as a level effect which will be fully captured by the parameterising CES coefficients. Therefore education can only be included outside of the labour nest, and we will use the quadratic specification for this to allow for both convexity and concavity of the return.

Having considered the role of human capital, with its twin dimensions of skills and schooling, in production, we will then undertake an analysis from the perspective of earnings. What are the implications of these production

functions for the return to schooling for workers, and how do they compare with estimates from earnings functions? If we assume that workers are paid their marginal products we can derive the relationship between earnings and the parameters of the production function. Taking the first derivative of Equation 4.15 with respect to the number of skilled workers implies that skilled wages should be given by:

$$w_s = MPL_s \quad (4.17)$$

$$= \frac{\partial Y}{\partial S} \quad (4.18)$$

$$= \beta_S A K_{it}^{\beta_K} S^{\beta_S-1} U^{\beta_U} I^{\beta_I} M^{\beta_M} e^{xX} e^{\delta_{s1}E_s + \delta_{s2}E_s^2 + \delta_{u1}E_u + \delta_{u2}E_u^2}. \quad (4.19)$$

A linearly homogenous production function can, to a monotonic transformation, be expressed in terms of only one input. Thus we can capture the effect of physical inputs on wages through the inclusion of a single element of the production function, such as the capital:labour ratio, along with a measure of A to give the scale.

Taking logarithms, we then have the implied Mincerian earnings function from Equation 4.15 as:

$$\ln w_s = \tilde{a} + \gamma_1 \ln A + xX + \gamma_2 \ln \frac{K}{L} + \delta_{s1}E_s + \delta_{s2}E_s^2 + \delta_{u1}E_u + \delta_{u2}E_u^2. \quad (4.20)$$

There is no tractable linear mapping from the CES production functions to a Mincerian earnings function; however, we can numerically calculate the marginal effects from the CES production functions and compare these with a quadratic approximation of the effects of education from an earnings func-

tion. Therefore, in the estimation of the earnings functions we will wish to include, as well as individual characteristics: firm characteristics (eg sector), the firm's capital:labour ratio, a measure of firm productivity, and measures of individual and firm-aggregate education.

The standard Mincerian earnings function aims to capture the return to skills through the inclusion of the number of years of schooling as an explanatory variable. However this standard approach does not fully capture the return to schooling as this is likely to differ by occupation. It is easy to conceive of a scenario where workers in skilled occupations receive a different return to some years of schooling than those in unskilled occupations. If the return differs by occupation, then the results from a pooled estimation would be biased. The available data on skills in our data set enables us to allow the return to schooling, and indeed the coefficients on other explanatory variables, to differ for skilled and unskilled workers. The modelling of the earnings function is described in more detail in Section 4.5.1. The following section describes the data that will be used for the analysis in this chapter.

4.3 Data

Summary statistics for the data are presented in Tables 4.1, 4.2 and 4.3. The analysis of this chapter uses the Ghanaian firm level data that has been exploited in previous chapters and so the details of the variable definitions and data construction are not repeated here unless new or of particular salience. The major additional piece of data is a survey of individual workers where this worker data can be matched to the firm data. This formed part of the

Ghana Manufacturing Enterprise Survey (GMES) collected by the Centre for the Study of African Economies, and is available on their website. The firms constituted a panel which was intended to be broadly representative of the size distribution of firms across the major sectors of Ghanas manufacturing industry. A sample of workers, at most 10 employees and 10 apprentices, was interviewed at each firm. The selection of workers within firms was stratified to ensure that reasonable numbers of workers of different occupations were included, and so skilled workers are over-sampled as they are a small fraction of the workforce. The availability of matched firm-worker data enables many more issues to be robustly addressed than with worker data alone. The firm level data we have is a panel, whilst the worker data is a repeated cross section of workers in those firms. Thus all discussion of fixed effects always refers to firm fixed effects. Due to the atypical characteristics of apprentices in Ghana these workers are dropped from the earnings function analysis.² In addition, females are also dropped from the sample to abstract from issues of the labour market participation of women.

In Chapter 2 labour input was considered homogenous - in that the physical quantities of labour input have been given by the number of employee-hours worked regardless of the work performed or the characteristics of the worker performing the task. Quality adjustment was by way of augmenting the production function by incorporating the average number of years of schooling of workers in the firm. Again, this has been done at the level of the firm, not differentiating between workers within the firm, and so has also been

²For example, 26% of apprentices receive no wages. A detailed analysis of the earnings of apprentices can be found in Monk et al. [2008].

making a homogeneity assumption or, more specifically, one of homotheticity and perfect substitutability. In Chapter 3 quantities of labour input were given by the number of employees multiplied by their average number of years of schooling. The return to education here was implicitly assumed to be common across all workers and constant for all years of schooling. In this chapter skilled and unskilled workers are differentiated in an attempt to understand more fully how skills impact upon firms and workers in Ghana. Workers are classified into eight occupations: managers, administrative and clerical, sales, supervisors, technical, production and support, apprentice masters, and apprentices. Workers in the first four categories are classified as skilled workers, while those in the latter four are classified as unskilled workers. Thus workers can be classified into skill categories independently of their schooling.

Earnings are real monthly earnings before tax in 1991 Ghanaian Cedis. *FirmAge* is the age of the firm in years, while $\ln \frac{K}{L}$ is the natural logarithm of the firm's capital:labour ratio in 1991 Cedis. *FirmFE* is a firm fixed effect extracted as the average of the error term for each firm. This was obtained from an OLS production function with quadratic education effects and constant returns in capital, labour, indirect and material inputs.³ The range of dummies for location, sector, year, unionisation and ownership are also included. The four location dummies take the value one if the firm is in Accra (the omitted category in the regressions that follow), Takoradi, Kumasi or the Cape Coast respectively. Similarly, the sector dummies are for firms in

³This method was chosen as the coefficients from this specification were the most similar to those obtained in Chapter 2 where closer attention was paid to the estimation of production functions. Extracting the estimates from a fixed effect estimation produced similar results.

the bakery, food, drink, textiles, garments, wood, furniture, machines, metal (omitted) and chemical sectors. The dummies *Anyfor* and *State* take the value one if the firm has any foreign or state ownership, respectively, while *Union* takes the value one if the firm’s workforce is unionised.

There are sixteen variables describing the family background of the worker. For each worker, *ProfDad* and *FarmDad* are dummies taking the value one if the worker’s father was a professional or a farmer respectively, and otherwise zero. *EducDad* is the number of years of education completed by the worker’s father. Similar definitions hold for *ProfMum*, *FarmMum* and *EducMum* in relation to the worker’s mother. The workers were also asked “what was the distance to the nearest Primary School when you were six years old?” and “what was the distance to the nearest Secondary School when you were twelve years old?” For each of these two questions the worker was able to choose between one of five categories: less than 1km, 1-3km, 3-6km, 6-10km and more than 10km. The first category is omitted for each question. The variable *dPrim2* is a dummy taking the value one if a worker lived between 1-3km from a Primary School when he was six years old and zero otherwise. Analogous definitions hold for *dPrim3*, *dPrim4*, *dPrim5*, *dSec2*, *dSec3*, *dSec4* and *dSec5*.

Educ is the number of years of completed schooling of each worker, *Age* is the age of the worker in years, while *Tenure* is the number of years the worker has been in a job with their current employer. Weighted averages of these variables were constructed for each firm for each year using the method described later in this section. From these firm-year averages, the variables *EduWgt*, *AgeWgt* and *TenWgt* are the corresponding time-invariant aver-

ages over all time periods for each firm, while $\Delta EduWgt$, $\Delta AgeWgt$ and $\Delta TenWgt$ are the period specific deviations from the firm mean in each time period. These decompositions allow the cross section and time series dimensions to be captured separately.⁴

The firm averages of *Educ*, *Age*, *Tenure* and all the variables in Table 4.3 were calculated using the occupational structure of the firm using all workers (ie including apprentices and women). For each firm we have the percentage of workers classified as being in each of the eight occupations. Where the occupational structure was missing for a particular time period, it was imputed with the firm specific average for all periods for which the occupational structure was available for that firm. Averages for each variable were then calculated for each firm/wave/occupation combination (for example, all production workers in firm 27 in 1995) for all cases where at least one worker of that firm/wave/occupation is observed. Missing values of the same variable for the same firm/wave/occupation combination were imputed with this average. For example, if there are three production workers observed in firm 27 in 1995 but we only know *Educ* for two of them, the third worker is assumed to have years of schooling equal to the average of these two values.

Further missing values exist as only a sample of workers was randomly interviewed from each firm, and so we do not necessarily observe a worker of each occupation from each firm. Where no workers of a firm/wave/occupation combination are observed, the value is assumed to be the average of that for all workers of that occupation in all other firms in that wave. For example, if

⁴This decomposition in earnings functions was also carried out implicitly by Van Biesebroeck [2007].

we do not observe any administrative staff from firm 27 in 1995, we assume they have characteristics identical to the average of all observed administrative workers in 1995. In 1994 and 1995, the family background of apprentices are not observed (i.e. the variables in Table 4.3). For these data points we replace the missing values with the mean of the firm/apprentice in the years for which it is observed. That is, we assume that apprentices in firm 27 in 1995 (wave 5) had the average value of *EducMum* as apprentices in firm 27 over all the years for which *EducMum* is observed.

We now have a set of variable averages by firm/wave/occupation, and the percentage of the workforce of each firm that is composed of each occupation type. Averages for each firm/wave are now computed as a weighted average of the firm/wave/occupation averages, where the weights are given by the workforce composition. The firm averages for education, age and tenure are used in the earnings functions directly to capture externalities, while the firm averages of family background are later used as instruments for education in a firm level production function.

Firms are classified into four size categories. Micro firms are those with less than 6 employees, small firms are those with at least 6 and less than 30 employees, medium firms are those with at least 30 employees and less than 100, while large firms are those with 100 employees or more. As was the case with the variables *EduWgt*, *AgeWgt* and *TenWgt*, these firm level variables are decomposed into two elements. One is the average of each dummy over the entire period for which the firm is observed; the other is the deviation of the value of the dummy in a particular period from this average. So a firm with 5 employees in 4 years and 6 employees for 1 year

would have $Micro = 0.8$, $Small = 0.2$, $\Delta Micro = 0.2, 0.2, 0.2, 0.2, -0.8$, $\Delta Small = -0.2, -0.2, -0.2, -0.2, 0.8$ and all other firm size variables equal to zero for all periods.

This transformation allows us to exploit the panel dimension of the data to differentiate between two different effects. The beauty of panel data is that we can exploit both the cross-sectional dimension and the time-series dimension. The cross-sectional variation tells us how the expectation of the dependent variable will differ between firms with different average levels of the explanatory variables. The time series dimension tells us how the expectation of the dependent variable will differ within a firm over time as the explanatory variables change. Without the transformation, these two effects are constrained to be the same. For the firm size variables, there is a further reason why such a transformation could be important. Transitory changes in firm size or measurement error resulting in firms switching from one size category to another will produce a bias in the estimated relationship between firm size and the dependent variable. Davis et al. [1996] propose using a measure of the average size over the observed periods to overcome this; providing a further reason for adopting this decomposition.

We have 6634 workers from 200 firms of which 2437 are classified as skilled and 4197 as unskilled. There are 39 firms who have no skilled workers and 3 firms who have no unskilled workers. On average, the workers are 38 years old, went to school for 10 years and have been in their job for 8 years. 60% live in Accra, 27% in Kumasi, 11% in Takoradi and the remaining 2% in the Cape Coast. The average worker works for a firm which has been operating for 20 years. 2% of the workers work for micro firms, 29% for small firms,

40% for medium firms and 29% for large firms. 23% of these workers are employed in the metals sector, 22% in the furniture sector, 16% in wood and 15% in food. Compared to unskilled workers, skilled workers are, on average, 6.5 years older and have 2 more years of tenure.

Table 4.4 breaks down the number of skilled and unskilled workers by number of years of schooling and also presents the predicted probability that a worker with a given number of years of schooling will be in a skilled occupation. The calculation of these probabilities is carried out in Section 4.5.2 but the results are included in this table for brevity. For both skilled and unskilled workers the modal number of years of schooling is ten. Almost all skilled workers have at least ten years of education, but most workers with at least ten years of education are not skilled. The vast majority of workers in this sample have completed at least primary school, although just under 8% of the unskilled workers have not attended school. This data will be used in the estimation of production functions in Section 4.4 and earnings functions in Section 4.5.

	Skilled		Unskilled		Total	
	Mean	s.e	Mean	s.e.	Mean	s.e.
ln(Earnings)	10.68	(0.05)	9.98	(0.03)	10.24	(0.04)
Earnings	58 567	(3 155)	25 999	(924)	37 963	(1 771)
Educ	12.84	(0.14)	9.77	(0.17)	10.90	(0.15)
Educ ²	174.14	(3.62)	108.00	(2.55)	132.30	(2.94)
EduWgt	10.93	(0.15)	10.39	(0.14)	10.59	(0.14)
Δ EduWgt	-0.05	(0.03)	0.02	(0.02)	-0.01	(0.01)
Age	41.72	(0.63)	35.10	(0.52)	37.53	(0.51)
Age ²	1 858.41	(56.56)	1 347.69	(41.00)	1 535.30	(41.64)
AgeWgt	36.78	(0.50)	34.50	(0.50)	35.34	(0.48)
Δ AgeWgt	0.21	(0.12)	0.08	(0.10)	0.13	(0.06)
Tenure	9.76	(0.53)	7.50	(0.41)	8.33	(0.41)
Tenure ²	166.68	(16.74)	105.33	(11.73)	127.87	(11.80)
TenWgt	8.17	(0.35)	7.55	(0.34)	7.78	(0.32)
Δ TenWgt	0.19	(0.09)	0.11	(0.07)	0.14	(0.05)
Firm Age	21.64	(1.52)	19.34	(1.03)	20.19	(1.14)
FirmAge ²	656.73	(101.98)	522.28	(60.35)	571.67	(73.26)
Micro	0.01	(0.00)	0.02	(0.00)	0.02	(0.00)
Δ Micro	0.00	(0.00)	0.00	(0.00)	0.00	(0.00)
Small	0.19	(0.03)	0.35	(0.04)	0.29	(0.03)
Δ Small	0.01	(0.01)	0.02	(0.01)	0.01	(0.00)
Δ Medium	0.03	(0.01)	0.02	(0.01)	0.02	(0.00)
Large	0.39	(0.05)	0.23	(0.03)	0.29	(0.04)
Δ Large	0.03	(0.01)	0.02	(0.01)	0.02	(0.01)
FirmFE	0.02	(0.03)	0.00	(0.02)	0.01	(0.02)
$\ln \frac{K}{L}$	14.40	(0.12)	13.74	(0.14)	13.98	(0.13)

Table 4.1: Sample means of the variables used in the earnings functions. The standard errors of the mean are given in parenthesis and are robust to correlation within firms. To transform these into standard deviations for the sample multiply by $\sqrt{N}$. Note that, even for the firm variables, the means are calculated over workers. Thus, for example, more than 1% of the firms will be micro even though only 1% of the workers are employed in micro firms.

	Skilled	Unskilled	Total
	Mean s.e	Mean s.e.	Mean s.e.
Accra	0.62	0.58	0.60
Takoradi	0.13	0.10	0.11
Kumasi	0.23	0.30	0.27
Cape	0.02	0.02	0.02
Bakery	0.01	0.05	0.04
Food	0.19	0.12	0.15
Drink	0.02	0.01	0.01
Textile	0.04	0.04	0.04
Garment	0.05	0.11	0.09
Wood	0.18	0.14	0.16
Furn	0.18	0.24	0.22
Machines	0.04	0.04	0.04
Metal	0.25	0.22	0.23
Chemical	0.04	0.02	0.03
Union	0.66	0.47	0.54
Anyfor	0.39	0.27	0.31
State	0.09	0.07	0.08
wave2	0.06	0.07	0.06
wave3	0.07	0.10	0.09
wave4	0.10	0.10	0.10
wave5	0.11	0.11	0.11
wave6	0.13	0.11	0.12
wave7	0.14	0.12	0.13
wave8	0.10	0.09	0.10
wave9	0.11	0.10	0.10
wave10	0.04	0.05	0.04
wave11	0.04	0.05	0.05
wave12	0.04	0.05	0.05
Obs	2437	4197	6634
Firms	161	197	200

Table 4.2: Descriptive Statistics for the firm dummies used in the earnings functions. Standard errors are not presented for these dummy variables. Note again that these summary statistics refer to the firm characteristics attached to the workers.

	Unskilled		Skilled	
	Mean (s.d.)	N	Mean (s.d.)	N
ProfDad	0.088	3792	0.124	2589
ProfMum	0.013	3792	0.026	2589
FarmDad	0.370	3792	0.374	2589
FarmMum	0.339	3792	0.344	2589
dPrim2	0.393	1727	0.354	1224
dPrim3	0.090	1727	0.083	1224
dPrim4	0.014	1727	0.013	1224
dPrim5	0.006	1727	0.009	1224
dSec2	0.331	1736	0.332	1236
dSec3	0.176	1736	0.135	1236
dSec4	0.060	1736	0.052	1236
dSec5	0.052	1736	0.077	1236
EducDad	5.871	3400	6.526	2392
	(5.621)		(5.730)	
EducMum	3.130	3586	3.547	2529
	(4.600)		(4.978)	

Table 4.3: Descriptive Statistics for the additional variables used in the earnings functions. Standard deviations are not presented for the dummy variables.

Schooling	Unskilled	Skilled	p_t
	1	2	3
0	328	24	0.000
1	0	0	0.001
2	4	0	0.002
3	22	0	0.003
4	35	4	0.006
5	15	4	0.013
6	89	12	0.024
7	29	0	0.045
8	51	10	0.082
9	363	40	0.140
10	2107	691	0.227
11	163	106	0.344
12	212	111	0.485
13	462	558	0.634
14	110	112	0.770
15	27	272	0.876
16	136	154	0.943
17	26	137	0.979
18	18	200	0.994

Table 4.4: Selected statistics by years of education. Columns 1 and 2 present the number of workers in each skill category with the specified number of years of education. For every level of education, Column 3 gives the predicted probability for a worker with otherwise average characteristics of being selected into a skilled occupation (from Equation 4.33).

4.4 Skills in the Production Function

We know that skills are used in different ways by firms in Ghana as compared to those in South Korea. In this section we exploit the matched firm and worker data in order to investigate in more detail how skills enter into the Ghanaian production function. In the Cobb-Douglas production functions used in Chapter 2, all types of workers were implicitly assumed to be perfect substitutes with each other and years of schooling were also perfectly substitutable between all workers. In this section this assumption of perfect substitutability is relaxed. We retain the Cobb-Douglas formulation for the four categories of inputs, but now consider labour input to be a CES aggregate of the number of skilled and unskilled workers and of their respective education levels.

4.4.1 Skills in a CES Production Function

Table 4.5 presents the means and standard errors for the variables used in the production functions in this section. These firms are a sub-sample of those used in Chapter 2 as workforce composition was not available for all firms. Non-linear estimation methods must be used to estimate the CES production function. Extensive investigation of the impact of endogeneity on the estimation of the Ghanaian production function has been carried out in Chapters 2 and 3. These previous results showed that the bias from unobserved firm characteristics being correlated with inputs is quantitatively small and qualitatively unimportant and, so, we do not control for endogene-

	South Korea	South Korea	Ghana	Ghana
	Mean	s.e.	Mean	s.e.
Output (Y)	32,929	(3,310)	3,360	(775)
Capital (K)	13,526	(2,289)	1,162	(325)
Skilled Workers (S)	83.4	(5.3)	13.0	(1.6)
Unskilled Workers (U)	39.4	(2.9)	62.0	(9.4)
Indirect Inputs (I)	451	(63)	652	(159)
Materials (M)	11,746	(1,280)	1,733	(458)
Education (yrs)	12.64	(0.07)	9.72	(0.14)
Obs	882		1615	
Firms	344		218	

Table 4.5: Means and standard errors for the variables used for the estimation in Section 4.4. S is the number of skilled workers and U is the number of unskilled workers. Other definitions are as previously defined with units for the monetary variables being '000 1996\$PPP.

ity here.⁵

We begin our analysis by considering Ghanaian firms. Column 1 of Table 4.6 presents the estimates from the most general form of the equation. Note that, as expected, the coefficients $\beta_K, \beta_L, \beta_I, \beta_M$ are similar to those obtained in earlier estimations, and are stable to different starting values. However, the estimates of the parameters $(\rho, \rho_s, \rho_u, b, c)$ are sensitive to initial values; suggesting that further structure needs to be imposed on the model. Testing the aggregator function for the restrictions in Equations 4.11 and 4.12 cannot be rejected and so they are imposed in Columns 2 and 3 respectively. However, neither of these restrictions produces satisfactory results. The estimates in Column 2 are stable to initial values, but the estimate of ρ is greater

⁵The GMM estimators used in previous Chapters have recently been applied to a nonlinear framework [Apergis, 2007]. However, there is extremely limited evidence as to the performance of system GMM estimators in a nonlinear framework and so, given that previous evidence has shown that endogeneity does not cause large biases in this data, this approach was not pursued.

than one (although imprecise). The estimates in Column 3 are sensitive to initial conditions and so cannot be reliably interpreted.

With these caveats in mind, the implied output elasticities of the number and average education of skilled and unskilled workers respectively are presented in Table 4.7. These are relatively stable across the three different CES specifications and suggest that education has little effect and the elasticities of the number of skilled and unskilled workers are around 0.08 and 0.09 respectively. Note that, in all of the CES specifications, we cannot reject the null hypothesis that $\rho = 0$. Due to the unsatisfactory performance of the CES estimations, we therefore proceed to adopt the Cobb-Douglas specification of Equation 4.15, the estimation of which will provide more robust estimates of the output elasticities of the components of total labour input.

A CES production function, of the form given in Equation 4.13, can also be estimated for South Korean firms. We do not have any information on the individual employees of the South Korean firms, but we do know the proportion of the workforce in each of six occupations: administrative, skilled, service/clerical/sales, technical, technical and related, and unskilled. A worker engaged in one of the first three occupations is classified as a skilled worker, while workers in the latter three occupations are classified as unskilled. Estimating Equation 4.13 with Equation 4.16 produces an estimate of ρ which is greater than one, even with constant returns to scale imposed, and the equation is badly identified. Imposing $\rho = 0$, which cannot be rejected with a p-value of 0.1936, gives us a Cobb-Douglas production which can be more robustly estimated, and is also consistent with the preferred specification for Ghana.

	1	2	3
	General Eq. 4.10	No Educ Eq. 4.11	CD Sub-Aggregates Eq. 4.12
A	2.7292***	3.1089***	2.6310***
(2)	(0.2425)	(0.1999)	(0.2530)
β_K	0.0409***	0.0398***	0.0440***
(0.05)	(0.0106)	(0.0109)	(0.0109)
β_L	0.1713***	0.2025***	0.1462*
(0.15)	(0.0460)	(0.0250)	(0.0707)
β_I	0.1446***	0.1422***	0.1498***
(0.16)	(0.0141)	(0.0143)	(0.0144)
β_M	0.6783***	0.6770***	0.6755***
(0.67)	(0.0180)	(0.0177)	(0.0177)
ρ	0.4787	1.7973	0.5450
(0.4)	(0.2603)	(1.2627)	(0.3144)
ρ_s	0.2637		1.0000
(0.01)	(0.6556)		(0.6035)
ρ_u	0.2773		0.9303*
(0.01)	(0.4742)		(0.3996)
a		0.9459***	0.6488***
(0.5)		(0.1096)	(0.1052)
b	1.2988*		
(0.5)	(0.5839)		
c	0.7892***		
(0.5)	(0.2294)		
Agewgt	-0.0022	-0.0053	0.0020
(0.01)	(0.0030)	(0.0030)	(0.0030)
Tenwgt	0.0104*	0.0095*	0.0100*
(0.01)	(0.0042)	(0.0041)	(0.0042)
CRS	0.4012	0.0002	0.8188
CD	0.5999		
Rho0	0.8384		

Table 4.6: The dependent variable is log of real output in 1996 \$PPP. Estimation of CES production functions using non-linear least squares. Note that ρ_s and ρ_u in Column 1 are as defined in Equation 4.10, while in Column 3 they are as defined in Equation 4.12. CRS is a test of the null of constant returns to scale. CD is a test of the null of Cobb-Douglas sub-aggregates. Rho0 is the p-value from a test of $H_0 : \rho_s = \rho_u = 0$. * 0.05 ** 0.01 ***0.001. Year dummies have been included but are not reported. Standard errors are clustered by firm. There are 1615 observations and 218 firms. The initial values for the non-linear estimation are as given in parentheses under the variable names, with the exception of Column 3 where the exceptions are $\rho_s = \rho_u = 0.5$, a test of which as the null has a p-value of 0.5412.

	1	2	3
	General Eq. 4.10	No Educ Eq. 4.11	CD Sub-Aggregates Eq. 4.12
S	0.0791** (0.0260)	0.1038*** (0.0271)	0.0670** (0.0270)
U	0.0953** (0.0275)	0.0988** (0.0286)	0.0737** (0.0270)
E_s	-0.0182 (0.0320)	- -	0.0000 (0.0411)
E_u	0.0150 (0.0103)	- -	0.0055 (0.0338)

Table 4.7: Implied output elasticities of the components of the labour sub-aggregates from the corresponding regressions in Table 4.6 evaluated at the mean.

4.4.2 Skills in a Cobb-Douglas Production Function

Table 4.8 presents the estimates for both countries from the Cobb-Douglas production functions with skilled and unskilled labour as separate inputs. Variable definitions remain as before, except that now the input L, the number of workers, is separated into two inputs S and U, the number of skilled and unskilled workers respectively. In Ghana, the mean (median) of the number of skilled and unskilled workers is 12.96 (2.22) and 61.98 (18) respectively. For South Korea the corresponding figures are 83.43 (51.16) and 39.42 (25.53) respectively.

The GMM estimates of β_S and β_U are not well identified in Ghana and the sign on β_U in South Korea is implausible and imprecise. As the OLS estimates for both countries appear reasonable based upon our previous investigations, we take the OLS estimates as our preferred ones in this case. Consider the relative magnitudes of the education parameters in Tables 4.8 and 2.2. The estimate of the return received by the firm when its workers

	1	2	3	4
	South Korea OLS	South Korea GMM	Ghana OLS	Ghana GMM
lnK	0.1197*** (0.0308)	0.3025** (0.1072)	0.0258* (0.0100)	0.0013 (0.0251)
lnS	0.3300*** (0.0346)	0.4787** (0.1521)	0.0326 (0.0176)	0.0627 (0.0359)
lnU	0.0726 (0.0376)	-0.1687 (0.1167)	0.0798*** (0.0174)	0.0844 (0.0453)
lnI	0.2257*** (0.0297)	0.0901 (0.0904)	0.1731*** (0.0142)	0.2116*** (0.0285)
lnM	0.2520*** (0.0380)	0.2973** (0.0957)	0.6886*** (0.0184)	0.6401*** (0.0372)
E	0.3996 (0.2577)	0.1185 (0.3015)	-0.0095 (0.0142)	-0.0156 (0.0196)
E ²	-0.0122 (0.0105)	-0.0040 (0.0118)	0.0010 (0.0009)	0.0013 (0.0014)
Constant	3.5164* (1.6461)	4.0719 (2.2408)	2.1495*** (0.1589)	2.5777*** (0.3311)
CRS	0.2597	0.0997	0.0003	0.1299
Educ	0.0001	0.8664	0.2814	0.5959
AR1		0.4125		0.0000
AR2				0.0001
AR3				0.9908
Sargan		18.0405		131.8078
Sargan df		21		126
Sargan p		0.6464		0.3438
Obs	882	882	1615	1615
Firms		344		218

Table 4.8: The dependent variable is log of real output in 1996\$PPP. Cobb-Douglas CRS production functions with skilled and unskilled labour as separate inputs for Ghana and South Korea. Year dummies are included but not reported. CRS is a p-value from a Wald test of the null that the production function is CRS. Educ is the p-value from a test of the null that the coefficients on E and E^2 are jointly zero. The $AR\#$ statistics are p-values from a test of the null that there is no $\#$ th order autocorrelation [Arellano and Bond, 1991], while the Sargan test is a test of the over-identifying restrictions: whether, as a group, the instruments appear exogenous. Equation 4.14 was estimated for Ghana and it was not possible to reject the null that the education coefficients were identical and so this was imposed to ensure consistency with the South Korean specification. Standard errors are robust to heteroskedasticity and autocorrelation, and those for the OLS regressions have been calculated using a clustering method that allows for the errors to be correlated within firms.

acquire, on average, an extra year of education is higher in Table 2.2 than in Table 4.8. As we would expect education to affect selection into occupations, it is not surprising that its impact on the output of firms conditional upon occupational structure is lower than the unconditional return. The conditional point estimate of the South Korean firm return to education is lower than the unconditional return, but both are still substantially higher than the corresponding return in Ghana. In Ghana this distinction in the occupational structure completely removes any effect of education on output, as it did in the CES specification. The small firm return to education in Ghana that was identified in Chapter 2 appears to be picking up the fact that firms with more skilled workers have a higher average level of education.

It may seem initially surprising that the output elasticity of unskilled workers is higher than that for skilled workers in Ghana. Recall that elasticities refer to the percentage change in output for a percentage change in the input and, as there are around five times more unskilled than skilled workers per firm in Ghana, a given percentage change in unskilled workers will be a much larger number of absolute workers than a similar change for skilled workers. What is clear is that the output elasticity of skilled workers is much lower in Ghana than it is in South Korea while that of unskilled workers is comparable. In terms of the responsiveness of output, then, the Ghanaian technology is much less effective in its use of skilled workers.

In a Cobb-Douglas production function, the coefficient on an input is not only equal to the output elasticity, but also to the cost share of that input in the corresponding dual cost function. We can use the inferred cost shares along with the observed proportions of worker types to calculate the wage

premium that skilled workers receive in each country. In South Korea, skilled workers are 68% of the labour force but receive 82% of the wages⁶, thus the ratio of skilled to unskilled wages can be loosely inferred as $\frac{82/68}{18/32} \approx 2.1$. Note that doing this calculation for Ghana would imply a skilled wage premium of $\frac{29/17}{71/83} \approx 2.0$ which corresponds almost exactly with the wage data in Table 4.1. This acts as a robustness check of our modelling procedure. It is striking that the inferred wage premium from being a skilled worker, conditional on human capital, is the same in both countries; although, the proportion of skilled workers in South Korean firms is substantially higher, as are their absolute wages. Note that this definition of the wage premium does not take into account worker or firm characteristics - it is simply the ratio of skilled to unskilled wages and does not necessarily tell us the additional earnings a particular individual would receive upon changing occupation. This latter aspect of the skill premium is discussed in Section 4.5.

Conclusions

In Section 4.4 we generalised several aspects of the firm level analysis presented in earlier Chapters. Skilled and unskilled workers, and their respective education levels, were distinguished as separate inputs and the functional form generalised to CES. Despite the additional flexibility, we still could not reject the Cobb-Douglas specification. After differentiating between skilled and unskilled workers, the return to education to the firm remains low in Ghana and much higher in South Korea: again, to the extent where this difference can almost fully account for the output per worker differential. The

⁶ $\frac{0.3300}{0.3300+0.0726} \approx 0.82$.

other major result of Chapter 2, that of technological heterogeneity, is also preserved with the generalisations of this section. Skilled workers make up a larger proportion of the workforce in South Korean firms, but, even accounting for this, the Ghanaian technology remains characterised by a low return to skills. The skill premium is similar in both countries; although, absolute wages are higher in South Korea.

4.5 Earnings Functions

In this section we use data on the earnings of individual workers in Ghanaian manufacturing firms to investigate the interplay between education, skills, firm productivity and earnings. Education can affect earnings through selection into a skilled occupation and also through increasing a worker's productivity conditional upon selection. We use data on occupational structure to separately identify the selectivity and productivity effects of education upon earnings. The availability of a matched data set on the firms employing these workers means that we can include a wide range of controls in the earnings functions.

4.5.1 Estimating Earnings Functions

The return to the firm of worker education in Ghana is low, and this is in large part behind the observed differences in output per worker between firms in Ghana and those in South Korea. Now we consider the impact of worker education at the individual level. We wish to estimate the impact of an individual's education on his earnings; that is, the return to education at

the worker level. Of males who are employed in the manufacturing sector, by how much will their earnings increase if they complete an additional year of schooling? We also seek to further separate out this impact into a selection effect and a productivity effect. Understanding how education impacts upon individual earnings will help us to understand the impact at the firm level.

It is not usual in the estimation of earnings functions for the occupation of the worker to be included. The rationale for this is that selection into a higher-paying occupation is part of the return an individual receives from education and so interest should lie in the impact of education on earnings unconditionally (with respect to occupation). However, when interest lies in the relationship between production and earnings then the conditional return is also important. To understand how production technology is linked to earnings it is necessary to identify how an additional year of education will affect the productivity of a worker aside from any selection effect. It is possible for the conditional return to education to be zero for all workers and the unconditional return to be positive: this will be the case if skilled workers have higher earnings and education increases the likelihood of being selected into a skilled occupation.

The occupational structure of the firm will be related to the production technology; with skilled workers being associated with more sophisticated tasks than the unskilled. Skills may be partly created by schooling, work experience and unobservable human capital. Wage differentials between occupations, combined with how education affects the probability of entry into a skilled occupation, will describe the selection effect of education. The marginal impact of education upon wages within an occupation will describe

the productivity effect. Comparing these magnitudes with the effect of education on firm output will allow the identification of rents from increased human capital and where they are flowing.

Let log earnings be given by w ; let $\mathbf{x}_1$ be a vector of exogenous variables that are deterministically affecting w (i.e. uncorrelated with unobserved variables in the earnings function); $\mathbf{x}_2$ be a vector of endogenous variables (i.e. affecting w in a deterministic way, but also correlated with the unobservables); $\mathbf{z}$ be a vector of exogenous variables that affect w only via their deterministic impact on $\mathbf{x}_2$ (i.e. instruments); and let $\mathbf{y}$ be the vector of unobserved variables. In our context, $\mathbf{x}_1$ includes variables such as age, tenure and firm level variables, $\mathbf{x}_2$ contains individual education, and $\mathbf{z}$ contains worker background and education supply variables. We seek to obtain a consistent estimate of β_2 in:

$$w = \mathbf{x}_1\beta_1 + \mathbf{x}_2\beta_2 + \gamma_{\mathbf{y}}\mathbf{y} + u, \quad (4.21)$$

where individual subscripts have been dropped and u is an i.i.d. error term.

If we think of $\mathbf{y}$ as ability then we have a standard endogeneity problem in the estimation of earnings functions. More able workers (i.e. those with higher levels of unobservable human capital) will earn a higher wage as employers reward their competence. However, they also acquire more education as completing a year of schooling will be easier (i.e. less costly) for them than it is for those who are less able. The key point is that the same unobserved factors that make a worker likely to have more education also make them more likely to earn a higher wage. This will lead to the OLS estimate of β_2

being biased upwards as it picks up some of the causal effect that is actually due to the unobservables. However, in the developing country case, it is not necessarily the case that the bias will be upwards or that its magnitude will be the same for all levels of the endogenous variable. If those workers who have fewer years of education also have a systematically higher return to education, then this will bias the coefficient downwards. This could be the case if those who have a high return to education have higher discount rates. Alternatively, such workers could be constrained in some way and have to exit schooling; for example, if their families cannot afford the direct and (current) opportunity costs of education. Such people may have entered school with lower levels of human capital than those who go on to complete more years of schooling, and so we may expect them to earn a higher initial return from the acquisition of additional human capital.

The causal effect of education on earnings, as well as the nature of the endogeneity bias, may differ by occupation and level of education. It may be that the particular additions to human capital gained when a worker stays for an extra year of schooling are only useful in skilled occupations, or that the skills learnt at different stages of education are differentially useful for skilled and unskilled occupations. For example, unskilled workers may receive a high return from the initial years of schooling but limited benefit once they have acquired basic literacy and numeracy. Conversely, compulsory schooling might add relatively little to the human capital of those who have high levels of ability, and so have a low return for skilled workers. For these reasons we include a quadratic effect in education and allow it to vary by occupation, our proxy for unobservable human capital.

The interplay between skills, education and earnings actually further complicates the endogeneity problem. Workers in skilled occupations will earn more; however, high ability workers are more likely to be selected into a skilled occupation. The situation is further complicated by the likelihood that education is also a determinant of occupation. Education, along with some or possibly all elements of $\mathbf{x}_1$, $\mathbf{z}$ and $\mathbf{y}$, can also be expected to impact upon selection into a skilled occupation as well as on the wage earned contingent upon occupation. In the econometric approach, the dual effect of unobservables on occupation and education will need to be accounted for and, possibly, exploited.

Three general approaches are taken to understand Equation 4.21: OLS, Heckman-style selection equations, and a two-part model where selection into an occupation and the determinants of earnings are considered sequentially. The reference case, being most efficient and unbiased in the case of no endogeneity, is OLS with heteroskedasticity consistent standard errors. Under the OLS approach, an earnings function is estimated for the entire sample of workers, as well as for skilled and unskilled workers separately. This approach will yield consistent estimates if all explanatory variables are exogenous and the marginal effects are common within the estimation sample. In previous chapters we have seen that, in many cases, firm level OLS estimates of the coefficients of production functions are only subject to small biases. In the context of education, this suggests that the average number of years of schooling of a firm's workforce is only weakly correlated with firm unobservables. However, at the individual level, we may expect endogeneity to be a bigger concern as individuals are more directly responsible for their

acquisition of human capital.

Note also that we will estimate Equation 4.21 both with and without an extensive set of firm and worker controls as described in Section 4.3. These may be part of either $\mathbf{x}_1$ or $\mathbf{x}_2$ but, as we are including them primarily as controls rather than to determine the correct magnitude of their coefficient, the distinction is not critical. It is important to compare the return to education both with and without these sets of controls so we can see how sensitive the estimates of the return are. If the estimates are sensitive it would be indicative that the controls are correlated with education.

The Heckman Selection Model

The Heckman model is motivated by the case where we only observe the variable of interest for some individuals, and that those we do not see are selected in a systematic way. The classic example is the estimation of women's wages: we only observe the wage offers of women who enter the workforce, but women do not make this decision randomly. Similar unobservables may drive both the selection and the wage offer equation, thereby producing biased estimates under standard OLS methods. The Heckman model can remove such bias if there are variables which affect the probability of being observed but not the outcome of interest. In our case, we observe workers in either skilled or unskilled occupations but we do not know what their wages would be if the same workers were in the other occupation. As we think that the process by which workers are selected into occupations is non-random and related via unobservables to our other explanatory variables, specifically to education, then we can view this as a Heckman selection model. The selection

equation is one into a skilled occupation, and we seek variables which affect this selection but do not directly affect the wage.

One additional problem that we have is that one variable that affects both selection and wages, namely education, is possibly endogenous in both equations. It is to be expected that education is an endogenous variable both in the selection equation and also in the earning function itself. If a worker has more education, then an employer may be more likely to appoint them to a skilled rather than an unskilled position. However this decision by the employer will also be affected by the perceived ability of the potential employee, which then makes education an endogenous variable if perceived ability is correlated to true ability and high ability workers self-select into more years of schooling. Education will have a direct effect on earnings if employees learn skills that improve their ability to undertake the job. However, their earnings will also be affected by their revealed aptitude for the job which, if correlated with general ability, will result in education being an endogenous variable in the wage equation.

Following the presentation of the Heckman [1979] model we can now reformulate our problem as a system of equations (dropping for simplicity the quadratic term in education):

$$w = \mathbf{x}_1\beta_1 + \beta_2educ + u_1 \text{ if } s = 1 \quad (4.22)$$

$$educ = \mathbf{z}\delta_1 + u_2 \text{ if } s = 1 \quad (4.23)$$

$$s = 1(\mathbf{z}\delta_2 + \delta_3educ + v_1 > 0) \quad (4.24)$$

where s is a dummy taking the value 1 if the worker is in a skilled occupation

and the vectors of exogenous variables $\mathbf{x}_1$ and $\mathbf{z}$ may share elements.⁷ An analogous system holds for modelling the wages of unskilled workers. We allow arbitrary correlation between u_1 , u_2 and v_1 and assume that

$$(u_1, v_1) \perp (\mathbf{x}_1, \mathbf{z}) \quad (4.25)$$

$$E(\mathbf{z}'u_2) = 0 \text{ and } \mathbf{z}\delta_1 = \mathbf{x}_1\delta_{21} + \mathbf{z}_2\delta_{22}, \delta_{22} \neq 0 \quad (4.26)$$

$$v_1 \sim N(0, 1) \quad (4.27)$$

$$E(u_1|v_1) = \gamma_1 v_1 \quad (4.28)$$

The first of these assumptions implies that $\mathbf{x}_1$ and $\mathbf{z}$ are exogenous in the selection and wage equations. The second assumption encapsulates the usual conditions on the instruments in that they are exogenous in the instrumenting equation, correlated with *educ*, and not present in the structural equation. The final two assumptions are functional form assumptions on the form of the errors which allows us to use the Heckman framework to deal with the selectivity bias. It should be noted that, as we have no information on the unemployed, the widest our population of interest can be is to include those in work. Our question of interest is, then: for those males who are in wage employment in manufacturing firms, how does education affect their occupation and earnings?

Estimation of Equation 4.22 will be biased not only because of the endogeneity of *educ* but also because we only observe w when $s = 1$ and, for the selected sample, $E(u_1|v_1) \neq 0$ effectively creating an omitted variable

⁷Ordinarily we would include all elements of $\mathbf{x}_1$ in $\mathbf{z}$ to avoid the imposition of unnecessary exclusion restrictions.

problem. We could estimate Equation 4.22 consistently if we could estimate:

$$w = \mathbf{x}_1\beta_1 + \beta_2 educ + E(u_1|\mathbf{z}, s) + e_1. \quad (4.29)$$

Now, by the definition of the sample and Equations 4.24, 4.27 and 4.28:

$$E(u_1|\mathbf{z}, s) = E(u_1|\mathbf{z}, 1), \quad (4.30)$$

$$= \gamma_1 E(v_1|v_1 > -\mathbf{z}\delta_2 - \delta_3 educ), \quad (4.31)$$

$$= \gamma_1 \lambda(\mathbf{z}\delta_2); \quad (4.32)$$

where $\lambda(\cdot) = \frac{\phi(\cdot)}{\Phi(\cdot)}$ and ϕ and Φ are the standard normal and standard cumulative normal densities respectively. This quantity was termed by Heckman as the Inverse Mills' Ratio (IMR). Thus, if we can get a consistent estimate of δ_2 we can calculate the omitted variable $\lambda(\mathbf{z}\delta_2)$ and put it into the structural equation and estimate using usual methods. In Heckman's original presentation these usual methods would be OLS but, in our case, we would use 2SLS as we have the endogenous variable *educ*. Similarly, a consistent estimate of δ_2 would usually come from a probit on Equation 4.24, but we need to use a probit with instrumental variables as *educ* is again possibly endogenous.

As we have endogenous variables and a selection issue, we need to ensure that we have enough variables to enable the equation to be identified. In the standard Heckman setup with no endogeneity, we need at least one variable that is in the selection Equation 4.24 but not in the structural Equation 4.22.⁸ With the endogenous variable *educ* we need, in addition, instruments that

⁸Technically this is not necessary as the function λ is non-linear but we would want to avoid identification based upon functional form assumptions.

are correlated with *educ* but which do not appear in the structural equation.⁹ We have sixteen variables on worker background that will be included as part of $\mathbf{z}$ (but not $\mathbf{x}_1$). Ten of these are education supply-side variables, namely, the dummy variables relating to the distance from the worker's home to the nearest primary school when the worker was six years old and the distance to the nearest secondary school at age twelve. These variables will be correlated with *educ* (children living further away from a school incur higher costs to attend and so will likely complete fewer years of schooling) but not with earnings and probably not with selection into a skilled occupation although, as noted, we will not impose this latter set of exclusion restrictions. We also have the 6 variables describing the occupational and educational background of the worker's parents. These variables should be uncorrelated with earnings (once I am in a job, my parents occupation will not determine my salary), but will affect selection into a skilled occupation, as well as possibly *educ*. Parental background variables are standard IVs for education, but how might they affect occupation? This could be through aspiration. If your parent is a professional or is more educated, then you are more likely to apply for a skilled job.

Thus our estimation procedure is as follows. In the selection Equation 4.24 we include $\mathbf{x}_1$ and the sixteen instruments but not *educ*.¹⁰ From this, we obtain a consistent estimate of δ_2 and construct λ . We then put this into the structural Equation 4.22 which is estimated using 2SLS with the

⁹At least two as we have a squared term in *educ*.

¹⁰We do not use a first stage but just include them all as exogenous variables, as at this stage we are not concerned with separately identifying the causal effect of education in the selection equation.

sixteen worker background variables and the exogenous vector $\mathbf{x}_1$ acting as instruments for *educ* in the first stage. We can test the null hypothesis $H_0 : \hat{\gamma}_1 = 0$ using a standard t-test. If the null is rejected, evidence exists of a selection effect. In the case of rejection the standard errors would need to be adjusted, beyond the usual robust calculation for heteroscedasticity, to account for the inclusion of the estimated parameter $\hat{\delta}_2$. This could be done, for example, through bootstrapping. These results from the estimation of the structural equations are presented in Tables 4.13, 4.14 and 4.15, while Column 1 of Tables 4.11 and 4.12 presents the estimation of the selection equation.

A range firm controls are included in these estimations, along with individual characteristics. In order to investigate whether the inclusion of these firm controls is affecting the estimates of the return to education, Table 4.10 presents the results of a regression with only the individual characteristics. In the event that the return to education is not independent of the firm controls, we can possibly identify the relevant characteristics describing the pattern of the return across firms. For example, if firm learning is important, then the exclusion of firm age might be expected to change the estimates of the return to education.

Modelling Selection and Earnings Distinctly

The importance of the selection effect can be evaluated by the significance of the IMR in the second stage of the Heckman procedure. In the event that the IMR term is insignificant, then we can conclude that there is no evidence of sample selection bias. In this case we can simply estimate earnings functions

over the two sub-samples, skilled and unskilled workers, and ignore the fact that we do not observe what the wage of an unskilled worker would be if he had a skilled occupation (and vice versa). These are the estimation results presented in Tables 4.16, 4.17 and 4.18. Selection can then be modelled separately using limited dependent variable techniques such as the probit equation presented in Column 2 of Tables 4.11 and 4.12. These Tables present the results of a probit estimation where the dependent variable is the dummy variable ‘skill’. Formally, the probit equation is:

$$P(skill = 1|\mathbf{x}) = \Phi(\mathbf{x}\beta) = \int_{-\infty}^{\mathbf{x}\beta} \phi(\mathbf{v})\mathbf{d}\mathbf{v}, \quad (4.33)$$

where ϕ is the standard normal density. To recover the marginal effects, we take the prediction from the probit equation and then evaluate the normal cumulative density function at that level.

It is necessary to make some additional exclusion restrictions when selection and earnings are modelled distinctly. In the estimation of Equation 4.24 we could simply include all the sixteen worker background variables regardless of whether we thought they were acting as instruments or as direct determinants of selection as we were only interested in a consistent estimate of the overall quantity λ rather than $\hat{\delta}_3$. In the sequential approach ignoring selection, we are now explicitly interested in the coefficient(s) on education in the selection equation and so it must be separately identified. The distance variables remain as instruments purely for education, as these supply variables should not determine subsequent selection into an occupation. The parental background variables are allowed to affect selection directly and,

like other exogenous variables in the equation, also act as instruments for education. In the selection equation we are imposing the exclusion restrictions on the distance variables but not on the parental background variables. This estimation is presented in Column 2 of Tables 4.11 and 4.12. Only a linear education term is included as the 2SLS procedure does not adequately identify both the linear and the quadratic terms.

Column 3 of Tables 4.11 and 4.12 controls for the endogeneity of education using a control function approach, which allows the detection of non-linearities in the selection effect of education (Monk et al. [2008] use this approach for Ghanaian apprentices). In this variation of the 2SLS approach, the first stage involves regressing the distance (education supply) variables and all other exogenous variables on education. The residual is then extracted. This residual will capture all the elements of education that cannot be explained by the exogenous variables and instruments ie including that part of education which is correlated to individual unobserved characteristics. Thus, when this residual is included in the second stage (the probit, in this case) it will mean that education can be treated as an exogenous variable, and the quadratic effect can be estimated.

Thus the estimation procedure becomes a sequential process where selection is modelled independently from earnings. First we estimate Equation 4.24 using both a 2-stage probit and a control function approach, using the distance variables as instruments for education and the parental background variables as explanatory variables. Secondly, we estimate a 2SLS procedure on Equation 4.22, with the first stage allowing for the endogeneity of education using the 16 worker background variables as instruments.

4.5.2 Results

The estimates from the regressions outlined in Section 4.5.1 are presented in Tables 4.9, 4.10, 4.11, 4.12, 4.13, 4.14, 4.15, 4.16, 4.17 and 4.18.* The implications of these estimates for each of our questions of interest are discussed below.

**Notes for these Tables:*

Background is a p -value from a Wald test of the null hypothesis that the coefficients on *EducDad*, *EducMum*, *FarmDad*, *FarmMum*, *ProfDad* and *ProfMum* are jointly equal to zero in the specified equation. *Distance* is a similar p -value, but for the variables *dPrim#* and *dSec#*. Where instrumental variables are used, the Anderson statistic is a test of the null that the equation is under-identified against the alternative that the equation is identified. It is a likelihood ratio test of whether the excluded instruments are correlated with the potentially endogenous variable. The Cragg-Donald statistic is a test of the null of weak instruments against the alternative that the instruments are not weak. Critical values can be found in Stock-Yogo [2005] but, for the results presented here, the critical values are always higher than the test statistic indicating that, in all cases, our instruments may be weak. *Reset* is a p -value from the null that the expected value of the dependent variable given the regressors is linear in those variables.

The Return to Education

Figures 4.1 and 4.2 show the sample average of log earnings by number of years of education for skilled and unskilled workers respectively. Columns 1 and 2 of Table 4.4 show, for every possible number of years of education, the number of workers in the sample with that number of years of education. From Table 4.4 we can see that, in this sample, almost all skilled workers have more than 10 years of education, but not all workers with more than 10 years of education end up in a skilled occupation. Comparing Figures 4.1 and 4.2 with Table 4.4, it can be seen that some of the visual outliers in

	All	Skilled	Unskilled
	1	2	3
OLS			
Educ	-0.0473*** (0.0102)	-0.0875*** (0.0184)	-0.0102 (0.0099)
Educ ²	0.0057*** (0.0006)	0.0067*** (0.0009)	0.0017** (0.0006)
Heckman			
Educ		-0.4223* (0.1691)	0.1788* (0.0840)
Educ ²		0.0187** (0.0060)	-0.0047 (0.0060)
InvMills		-0.1338 (0.1796)	-0.2747 (0.1551)
IV 2SLS			
Educ		-0.3644* (0.1502)	0.3023** (0.0959)
Educ ²		0.0171** (0.0058)	-0.0140* (0.0064)

Table 4.9: The dependent variable is log of real earnings in 1991 Cedis. Only the coefficients on education and the inverse Mills' ratio are reported here: see Appendix 4.A for the full estimates and diagnostic statistics. The OLS results are those from Table 4.13.

OLS	All	Skilled	Unskilled
	1	2	3
Educ	-0.0394*** (0.0056)	-0.0883*** (0.0189)	0.0028 (0.0060)
Educ ²	0.0063*** (0.0003)	0.0078*** (0.0007)	0.0018*** (0.0004)
Age	0.0743*** (0.0042)	0.0867*** (0.0082)	0.0665*** (0.0048)
Age ²	-0.0007*** (0.0001)	-0.0008*** (0.0001)	-0.0007*** (0.0001)
Tenure	0.0058* (0.0027)	-0.0026 (0.0043)	0.0127*** (0.0032)
Tenure ²	0.0000 (0.0001)	0.0002 (0.0001)	-0.0002 (0.0001)
Takoradi	-0.1309*** (0.0231)	-0.0944* (0.0379)	-0.1546*** (0.0267)
Kumasi	-0.0946*** (0.0167)	-0.1777*** (0.0306)	-0.0910*** (0.0180)
Cape	-0.4046*** (0.0454)	-0.4302*** (0.0766)	-0.4464*** (0.0517)
Constant	8.0452*** (0.0894)	8.2473*** (0.2104)	8.3609*** (0.0952)
Obs	8049	3113	4936

Table 4.10: The dependent variable is log of real earnings in 1991 Cedis. These are earnings functions for Ghana without any firm controls included. Year dummies are included but not reported.

	Selection Probit	IV Probit	Control Probit
	1	2	3
Educ		0.3499*** (0.0804)	0.1763* (0.0815)
Educ ²			0.0082*** (0.0014)
Age	0.1600*** (0.0258)	0.0145 (0.0448)	0.0144 (0.0424)
Age ²	-0.0014*** (0.0003)	0.0002 (0.0005)	0.0002 (0.0005)
Tenure	-0.0097 (0.0175)	0.0038 (0.0126)	0.0068 (0.0119)
Tenure ²	0.0002 (0.0005)	0.0002 (0.0003)	0.0001 (0.0003)
Takoradi	0.0872 (0.2159)	-0.0627 (0.1077)	-0.0824 (0.1032)
Kumasi	-0.2185 (0.1261)	0.4834** (0.1714)	0.4514** (0.1624)
Cape Coast	0.5592* (0.2667)	1.0126*** (0.2029)	1.0067*** (0.1929)
wave9	-0.0405* (0.0159)	-0.0552 (0.0767)	-0.0557 (0.0731)
wave10	0.1285 (0.0964)	0.1215 (0.1005)	0.1175 (0.0954)
wave11	0.0795 (0.0972)	0.0722 (0.0996)	0.0632 (0.0947)
wave12	0.0372 (0.1010)	0.0105 (0.1006)	0.0054 (0.0956)
Resid			-0.1427 (0.0766)
Overid		0.4223	
Exog		0.0599	
Background	0.0000	0.0302	0.0302
Distance	0.2334		
Obs	2627	2611	2611

Table 4.11: The dependent variable of these Probit regressions is the dummy variable taking the value one if the worker is in a skilled occupation. Column 1 is the first stage of the Heckman procedure, Equation 4.24. Column 2 includes *educ* as an endogenous variable and uses the distance variables as instruments. Overid is a p-value from a Wald test of the null that the over-identifying restrictions of the instrumenting are valid, while Exog is a p-value from a Wald test of the null that *educ* is actually exogenous. Column 3 uses a control function approach to allow for the endogeneity of education with a quadratic effect. Resid is the residual from the 1st stage control function. These results are continued in Table 4.12.

	Selection Probit	IV Probit	Control Probit
	1	2	
ProfDad	0.1354 (0.1744)	0.1386 (0.1162)	0.1429 (0.1112)
ProfMum	0.7875** (0.3051)	0.2723 (0.3305)	0.2394 (0.3169)
FarmDad	0.1950 (0.1155)	0.2453** (0.0848)	0.2325** (0.0805)
FarmMum	-0.0562 (0.1140)	-0.0837 (0.0814)	-0.0663 (0.0772)
EducDad	0.0254* (0.0104)	-0.0058 (0.0123)	-0.0065 (0.0116)
EducMum	0.0428*** (0.0112)	0.0118 (0.0111)	0.0096 (0.0107)
d6Prim2	-0.1283 (0.1638)		
d6Prim3	0.0191 (0.2030)		
d6Prim4	0.2458 (0.3947)		
d6Prim5	-0.0415 (0.4844)		
d12Sec2	0.0849 (0.1636)		
d12Sec3	-0.2338 (0.1938)		
d12Sec4	-0.4403 (0.2862)		
d12Sec5	-0.0281 (0.2187)		
Constant	-4.4486*** (0.5540)	-5.4356*** (0.4289)	-4.5469*** (0.4294)

Table 4.12: The dependent variable of these Probit regressions is the dummy variable taking the value 1 if the worker is in a skilled occupation. Column 1 is the first stage of the Heckman procedure, Equation 4.24. Column 2 includes *educ* as an endogenous variable and uses the distance variables as instruments. These results are a continuation of those presented in Table 4.11.

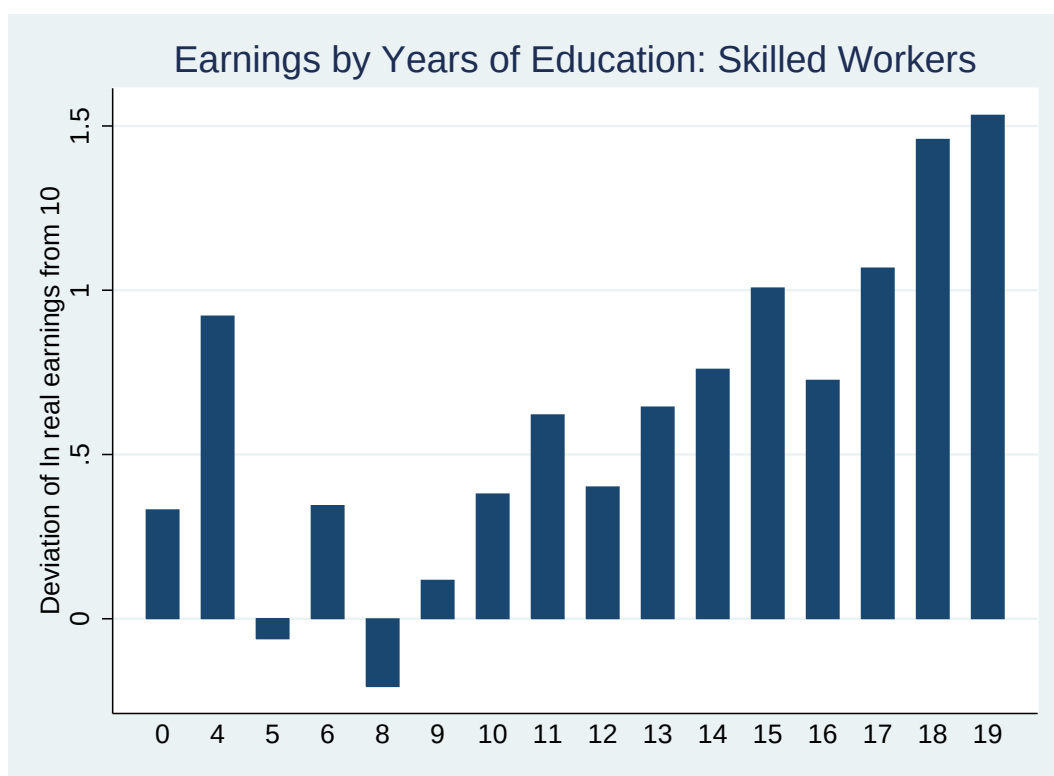


Figure 4.1: Sample means of log real earnings before tax in 1991 Cedis for skilled workers by number of years of schooling. The bars show the deviation of log real earnings from 10.

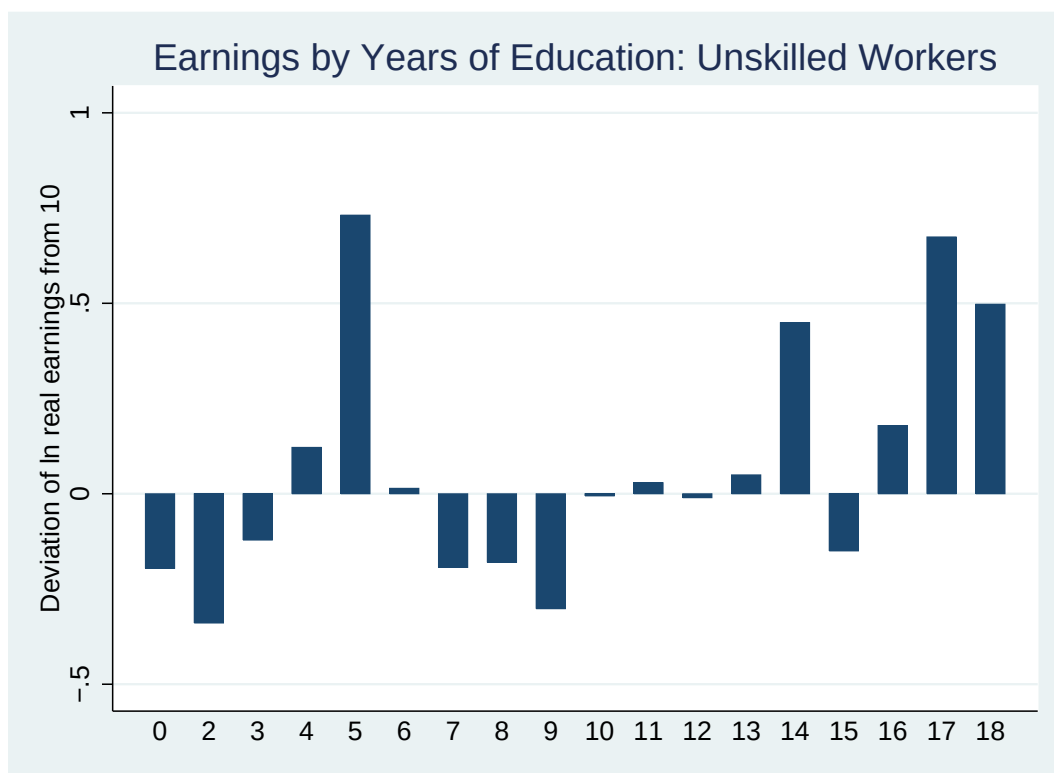


Figure 4.2: Sample means of log real earnings before tax in 1991 Cedis for unskilled workers by number of years of schooling. The bars show the deviation of log real earnings from 10.

the figures come from cohorts with very low numbers of observations, such as skilled workers with four years of education or unskilled workers with five years, and so can be expected to not unduly affect the estimates.

Using our data we are able to identify three elements of the effect of education on workers' earnings. The data contains a panel of firms but only a repeated cross-section of workers. Thus we can identify the effect of individual education in the cross-section, the effect of firm level average education in the cross-section, and the effect of firm level average education over time. Our interest lies primarily in understanding this first quantity. The latter two quantities are often used to capture human capital externalities at the firm level as they represent the apparent impact on an individual's wages if other workers in the firm have more education. However, an interpretation of these as pure externalities is not possible in this case as they are possibly endogenous. Unobserved firm characteristics affecting productivity will increase the wages of a worker while also being likely to attract a more educated workforce. Hence we have controlled for the effect of any firm level human capital externalities but the coefficients are not interpretable as estimates of the magnitude of these effects.

There are a number of variables relating to the firm included in the earnings function. The estimates of the individual's return to education with these controls is presented in Table 4.9 while the estimates when these controls are dropped are presented in Table 4.10. The return to education for skilled workers is virtually identical in the two specifications. For unskilled workers, while it is not possible to reject the null that the return is the same in both cases, the point estimate of the return is lower when the controls

are included. This implies some correlation between firm characteristics and the education of the unskilled. More particularly, the number of years of schooling of the unskilled is positively correlated with those firm characteristics associated with higher wages, such as being employed in a larger firm. However, the magnitude of this effect is small and insignificant. That there is little difference when firm controls are included implies that firms pay different levels of wages depending upon their characteristics, but the (average) marginal effect of education on wages is not affected by these characteristics. The investigations in previous chapters have shown that Ghanaian firms are homogenous in their use of technology and so, as we expect that technology is a determinant of the return to education, this result is not surprising. There would appear to be rents available from selection into a firm with favourable characteristics.

A graphical presentation of the estimated return to education from Table 4.9 is given in Figure 4.3. This figure gives the predicted earnings for an unskilled worker with mean characteristics and a skilled worker with mean characteristics allowing only the years of education to vary. Mean characteristics for each skill type are taken from Tables 4.1 and 4.2. The returns are presented for each of the three estimation strategies outlined above: OLS, Heckman and IV. The return for skilled workers is convex, while that for unskilled workers is concave or virtually linear. Regardless of the estimation method, we can say that skilled workers receive, at best, a low return for the first ten years of schooling, but then receive a positive return of approximately 11.4% for each additional year of education.¹¹ Unskilled workers,

¹¹This is the average return over the range 10-18 years of education for a skilled worker

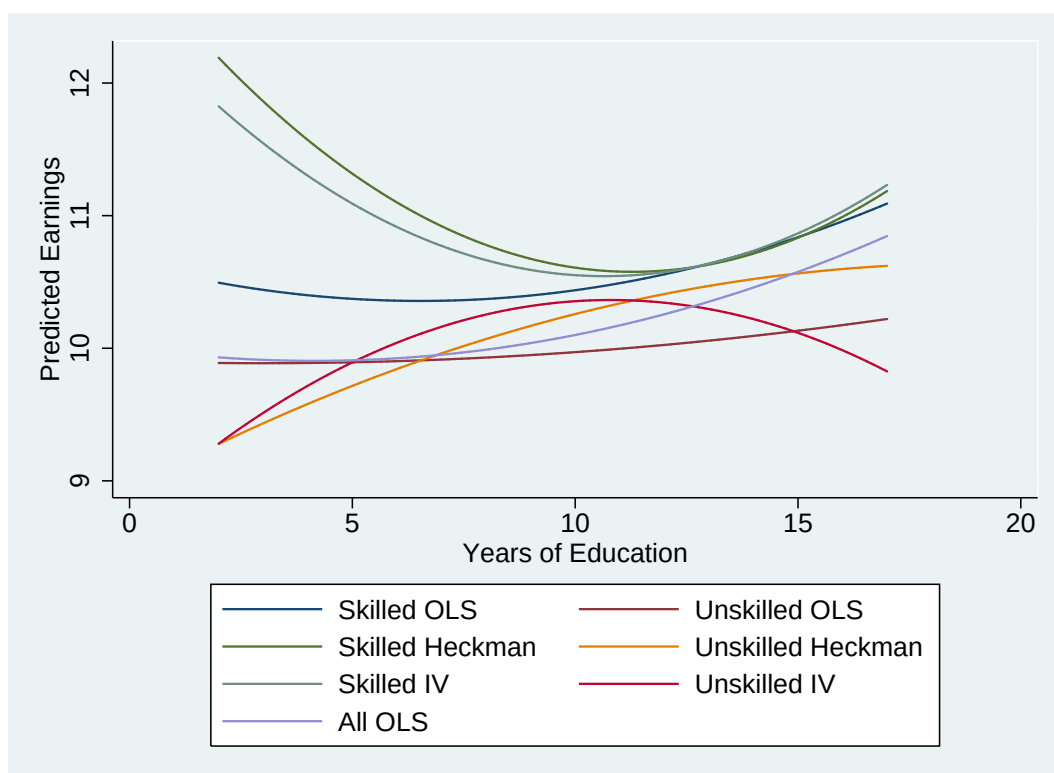


Figure 4.3: The return to education functions for Ghanaian skilled and unskilled workers as implied by Table 4.9. Predicted earnings are in logs of 1991 Cedis. Worker and firm characteristics, other than years of schooling, are assumed to be equal to the mean of all workers in the given skill category.

on the other hand, receive a small positive return for the first ten years of education after which the return does not rise.

A pooled OLS regression, as in Column 1 of Table 4.13, could be biased for at least two reasons. First, it incorrectly imposes the same return to education on skilled and unskilled workers. Because those with few years of education are unskilled and those with more education are mostly skilled, the implied return from the pooled OLS regression is much higher than that which either type of worker actually receives. This effect can be clearly seen in Figure 4.3, and is suggestive that the pooled OLS results are driven by pooling the two worker types. The pooled OLS line tracks that for unskilled workers at low levels of schooling and that for skilled workers at higher levels. The higher implied rate of return comes mainly from the level difference in wages of the skilled and unskilled, and partly from the higher rate of return experienced by the skilled for tertiary education. The second reason arises from possible endogeneity bias due to unobserved characteristics being correlated with the number of years of schooling.

The estimates of the coefficients on education for skilled workers in Tables 4.13 and 4.16 appear to be very different. However, once these different implied quadratics are graphed in Figure 4.3 we can see that, for the number of years of schooling relevant to almost all skilled workers, there is very little difference in the return to education across the three estimation methods. The average return over the range 10-18 years of education is 10-11% per year. The Heckman and IV estimates for skilled workers show a large decreasing return for the first years of education, while the OLS estimates show an

using the IV estimates in Table 4.16. Using the OLS estimates this return would be 10.0%.

essentially zero return. Which of these estimates should we believe? The OLS estimates are more consistent with the average pattern suggested by Figure 4.1, and the standard errors around the Heckman and IV coefficients are large. The relatively small numbers of skilled workers with very few years of schooling should make us wary of the unexpected result of a negative return in this range for some estimation methods. It is more likely that this is the result of the extrapolation of small differences in the convexity of the return to post-compulsory schooling into ranges with few observations.

If we were to believe the instrumented results for the first ten years of schooling, how could they be explained? Such a large negative return could be explained through a signalling story whereby workers only drop out of school because they are convinced of their own ability to get a skilled job on the basis of unobservable human capital. Although, more plausibly, those who do not complete compulsory education (eight years in Ghana over most of this period) are doing so because their families cannot afford it, rather than because they are signalling their ability. The IV results suggest that those who drop out have higher ability even than those who end up completing tertiary education. If credit constraints are not positively correlated with ability, it would be more reasonable to argue that they should do no better on average than those who complete compulsory schooling. Most of the weight of the observations is in the range 10-18 years, and here there are very small differences in the quadratics for the range relevant to the vast majority of skilled workers. The instrumented equations imply that the OLS estimates of the return to education for skilled workers over the relevant range are not substantially biased, and hence that there is limited endogeneity bias

from education being correlated with unobservables once selection into a skilled occupation has been taken into account. In addition, the IMR term is insignificant which implies that selection is not biasing the estimates. This is consistent with occupation being a good indicator of unobservable human capital. Thus we conclude that, in line with the OLS results, skilled workers gain no return for compulsory schooling, but then experience a return of approximately 10% per annum for post-compulsory education.¹²

For unskilled workers, the different estimation techniques do not have such coincident implications. The coefficient on the IMR in the Heckman results is insignificant, suggesting that estimation just on the sample of unskilled workers is not introducing a selectivity bias. So we focus attention on the OLS and IV results and ask the question ‘is endogeneity biasing our estimates of the return to education and, if so, do our instruments work?’ Addressing the latter question first, we consider the diagnostics. The Sargan test suggests the instruments are valid, while the Anderson tests indicates that, with our instruments, the equation is not under-identified. However, the Cragg-Donald statistic is suggestive of weak instruments: that is, even though our instruments are correlated with education, they are only weakly correlated. As noted by Stock and Yogo [2005] this is relatively problematic for IV estimators. So, while not rejecting the instruments, the diagnostics are not compelling evidence as to their validity and efficiency in this context.

Is it likely that endogeneity is causing a serious bias in the earnings function for unskilled workers? Recall that our instruments for education in the

¹²Compulsory schooling is eight years but this is partway through lower secondary school, the final year of which is the modal outcome of ten years of schooling. Thus when we refer to ‘compulsory schooling’ it should be taken to be the first ten years.

IV estimates are the distance from school the worker lived when six and twelve years old, and the occupational and educational background of the worker's parents. The reason for being concerned about endogeneity is the idea that those who are less able will complete fewer years of schooling as the effort required is higher than that required by a more able worker. In Ghana, a more likely reason for compulsory education not being completed is financial constraint. Less than 10% of workers in our sample have eight or fewer years of schooling (from Table 4.4) and, while the numbers in each cohort are relatively small, we can see from Figures 4.1 and 4.2 that the raw earnings outcomes for those workers varies widely with some cohorts doing better even than some of those with tertiary education. These descriptive statistics are suggestive that those leaving education early are not less able than others, consistent with the alternative hypothesis that budget constraints determine who does not complete compulsory schooling. If this is the case, then there will be no endogeneity problem with education and OLS estimation will be consistent. Given that unobserved ability was not severely biasing the estimates of the return to education for skilled workers, it is likely that the bias is, at worst, the same for unskilled workers. Our conclusion that OLS estimates are preferable is not unique. There are large numbers of published econometric studies which consider the issue of endogeneity. The consensus from this literature is that there is little, if any, bias in OLS estimates from unobserved ability [Card, 1999, Krueger and Lindahl, 2001].

While the shape of the return to education function for unskilled workers in Figure 4.3 differs by estimation method, calculations suggest that, on average, any bias is small. The implied average return from the 5th to the

15th year of education is almost identical for the OLS and the IV estimates, it is just that the OLS estimates have a low return over the entire range, while the IV estimates show a positive return up to ten years and then a negative return thereafter. If endogeneity is a problem and the instrumenting is being effective, then the concavity of the IV results implies that, controlling for ability, continuing beyond ten years of schooling actually decreases earnings for an unskilled worker. How could this be consistent with any unskilled workers staying at school for more than ten years? If a worker knew that he would end up with an unskilled job, he would leave school after ten years. But, *ex ante*, the worker does not know what kind of job he will get and so must be staying at school with the hope of being selected into a skilled occupation and so reaping the benefit from tertiary education that skilled workers receive. As will be discussed in Section 4.5.2, more years of education does increase the probability that you end up in a skilled occupation. Thus we can explain why some unskilled workers have more than ten years of education even though the return they receive *ex post* is so low.

Even so, this logic does not explain why earnings would fall, it merely suggests how no increase could be a plausible outcome. Given the weakness of the instruments and the relative unimportance of the endogeneity problem for skilled workers, it would be unwise to read too much into the suggestion of strong concavity made by the IV estimates. Rather, we conclude that the return to post-compulsory education is simply low for those who end up in unskilled occupations. Taking averages from 5-10 years as a proxy for the return to compulsory education, in order to avoid the quadratic extrapolation into areas with few observations, we have an annual return to compulsory

education of 0.8% using the OLS or 4.6% using the IV.¹³ Given our skepticism about the effectiveness and necessity of the instruments, we expect the true return to be at the lower end of this range.

Skills can be acquired through formal education, but also through work experience. Work experience can be divided into two categories: tenure in the current job, and total time in the labour force. The return to tenure is low, at around 1% per annum, and there is little evidence that it is significantly different from zero. Abstracting from periods of unemployment, age can be used as a proxy for total work experience. The return to age is significant and has a convex impact upon earnings. For a worker who begins work at age 15 and works continuously, the return to experience, using the OLS results in Table 4.13, begins at 4.6% if the worker is in a skilled occupation and 3.7% if in an unskilled occupation. These rates of return decline linearly until reaching zero at age 53. The return to experience compares very favourably with the return to education, implying that the opportunity cost of education is relatively high not only in terms of foregone earnings but in terms of increases in future salary.

The results of this section indicate that the bias from incorrectly pooling skilled and unskilled workers is larger than the bias from any possible endogeneity of education conditional on selection. This may be because correlation between unobserved characteristics and years of schooling is unimportant, or indicative that the relevant unobserved factors are operating through selection into occupations and so have been appropriately captured by our methodology.

¹³Calculated as $\frac{1}{10}(\hat{w}|(educ = 10) - \hat{w}|(educ = 5))$.

There is only a very small return to compulsory education, both for skilled and unskilled workers. For skilled workers only, post-compulsory education gives a return of approximately 10% per annum, comparable to the average return received by South Korean workers (assuming wages reflect marginal products) over all years of education. The convexity of the return to education that was observed in the production functions of Chapter 2 is mirrored in the earnings functions. Skills impact upon earnings; however, education is not effective at creating these skills. Education creates skills that impact upon earnings only for skilled workers and only during post-compulsory education.

Selection into Occupations

The return to education differs between those who end up being selected into a skilled occupation and those who end up being selected into an unskilled occupation. In order to properly understand the impact of education upon earnings, we need to understand the impact of education upon selection. For this we consider the results in Columns 2 and 3 of Tables 4.11 and 4.12. These are probit estimations on the dummy variable ‘skill’, which takes the value one when the worker is in a skilled occupation.

The impact of education on selection is consistent across Columns 2 and 3. The marginal impact of an additional year of education in Column 3, evaluated at the average ten years of education, is almost identical to the estimate of the linear effect in Column 2.¹⁴ Within the functional form re-

¹⁴The marginal effect of education on selection is given by Column 3 of Equation 4.11 as $0.1763 + (2 \cdot 10 \cdot 0.0082) = 0.3403$.

strictions imposed by the probit specification, Column 3 is indicative of a convex effect of education on selection. For a worker with mean characteristics, the probability of being in a skilled occupation as a function of education is given in Figure 4.4 and in Table 4.4 from which we see that, for levels of education around the sample mean, each additional year will increase the chance of ending up in a skilled job by around 10%. Those completing up to ten years of schooling do not receive substantially improved odds of getting into a skilled occupation. Post-compulsory education rapidly improves a worker's chance of getting a skilled job, although the benefit tails off after the completion of an undergraduate degree.

The effect of education in the production function was not significantly different from zero for Ghanaian firms, either using the CES or the Cobb-Douglas specification, suggesting that worker education does not affect the productivity of Ghanaian firms. Individuals, particularly skilled workers, do receive some return to education. These two facts combined tell us that the return on education to individuals comes mostly through the increased odds of selection into a skilled occupation. This, combined with the earnings functions of Section 4.5.2, allow us to conclude that increased wages and experiencing a reasonable return to education come from selection into a skilled occupation. This implies that output per worker and the return to education can be improved in Ghana by increasing the supply of skilled jobs. This cannot be done simply through the creation of more firms. South Korean skilled workers earn more than Ghanaian ones, and so creating more of the same skilled jobs will not close the output per worker gap. In addition, we know from Section 4.4 that the proportion of skilled workers per firm is much

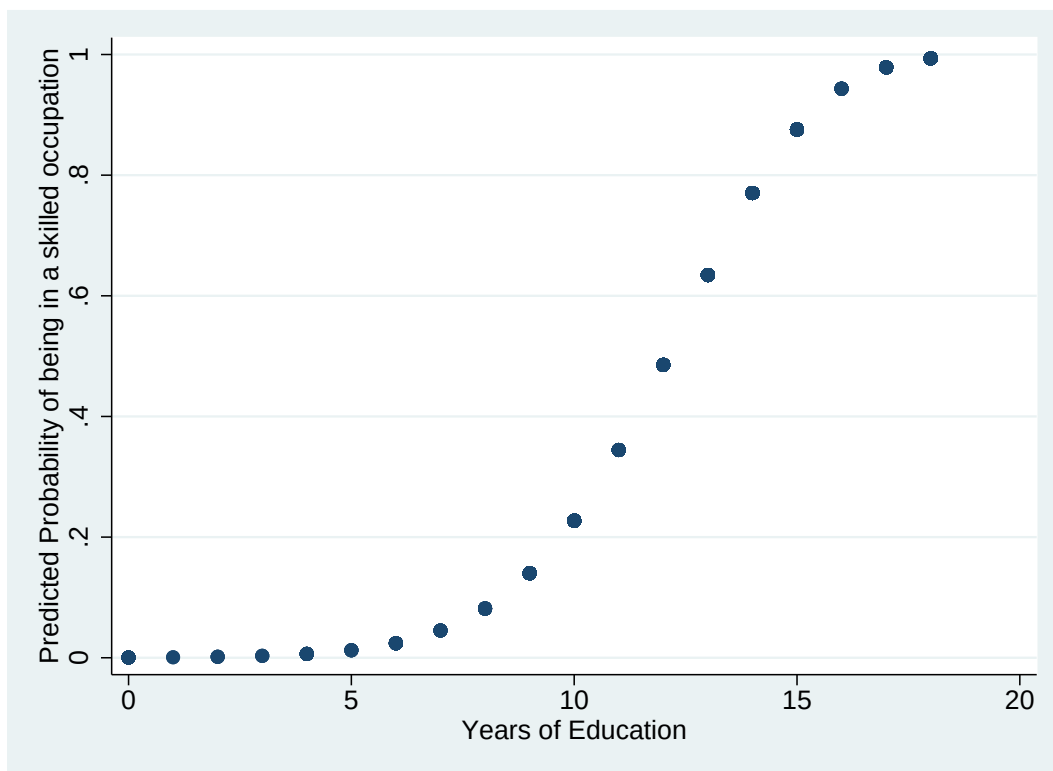


Figure 4.4: The predicted probability of being in a skilled occupation given average worker characteristics and varying the number of years of schooling using the results of the probit equation presented in Column 3 of Tables 4.11 and 4.12.

lower in Ghana. These facts combined tell us that a change in production technology would be required.

Worker and Firm Characteristics

While our primary interest has been on the impact of education on a worker's earnings and occupation, there are many other variables of interest contained in our data. The estimates of the parameters associated with these variables are presented in the Tables in Appendix 4.A. For many of these variables endogeneity will be a concern: workers may select into firms based upon their

characteristics. For example, if able workers prefer to work for larger firms because they see greater opportunities for promotion, then the coefficient on *Large* in the earnings function will be biased upwards. Instruments for such variables, e.g. a variable affecting whether a worker is in a large firm but not correlated with unobserved characteristics, would be difficult to find. These firm characteristics have been included as controls and, as we have no available instruments, the coefficient cannot be interpreted as causal.

As has been documented elsewhere [Söderbom et al., 2005], earnings vary substantially by firm size. While we have not conducted a robust investigation of firm size, the controls that have been included are consistent with firm size effects. Using the definitions described in Section 4.3 we again generate variables to account for the average size of the firm, and for changes in firm size between periods. Earnings increase with firm size with one exception: skilled workers in micro firms do better than those in small firms and equally as well as those in medium firms. Many skilled workers in micro firms will be owners classifying themselves as managers, and so this may be due to the misreporting of capital income as wages or simply that they are able to capture a larger share of firm rents than skilled workers in larger firms. The variables indicating change in firm size (according to our classifications) are not significant, but the signs are reasonable with firms that become micro (ie shrink) having lower wages than average and those growing to become large firms having higher wages. The fact that the variables in deviations are not significant implies that there are not firm threshold effects for wages at the levels used here, but that the difference is due to the cross-sectional variation in size rather than changes within firms. These suggestive firm size effects

are quantitatively large. Compared to a corresponding worker in a medium firm, unskilled workers in micro firms and skilled workers in small firms earn around 40% less while all workers in large firms earn around 30% more. This is even after controlling for all the firm variables in Tables 4.1 and 4.2 such as capital-labour ratios, sector, ownership and firm-average human capital. But note that the estimates of the marginal return to education are substantively unaffected by the inclusion of these controls for firm size.

Human capital differences, and externalities in particular, are widely believed to be a critical determinant of cross-country income differences. Many growth models, particularly those in the tradition of Lucas [2002], invoke human capital externalities as a mechanism. Any such externalities operating at the firm level¹⁵ will be captured by the firm-average levels of worker education, age and tenure and, if we were able to address endogeneity concerns, these could be used to obtain estimates of the size of externalities. If one takes the view that endogeneity is likely to bias these coefficients upwards, due to unobserved factors attracting both able and educated workers to firms, the estimates presented in Appendix 4.A could be viewed as upper bounds.

How large an externality would be required to explain the observed global distribution in income per capita? Acemoglu and Angrist [1999] note that in 1985, even using a common global private rate of return to education of 10%, this implies that the output per worker gap between countries in the

¹⁵Firm level externalities may be less important than those at a regional or national level. This is because firms are able to internalise these externalities in their wage offers and decisions of which workers to hire. However, if human capital externalities operate through proximity and human interaction then the level of the firm may be important.

top decile of schooling and the bottom decile should be around a factor of two (as the difference in average schooling between these two deciles is less than eight years). The observed gap of around fifteen times requires a rate of return of more like 35% implying that the social return, exclusive of the private return, would need to be at least 25% per annum. This figure is substantially higher than any of the estimates on firm average human capital in Appendix 4.A. With the caveat that we have not controlled for possible endogeneity of firm average human capital, our evidence is consistent with the consensus in the literature that there is limited evidence for substantial human capital externalities [Topel, 2005, Lange and Topel, 2006].

Consider now the other firm level variables. Unskilled workers in firms with older workers earn less, as do skilled workers in firms where workers have higher tenure. Earnings also vary by sector. Compared to the omitted sector, metals, skilled workers in the bakery and drinks sectors earn approximately 30% more, while those in the garments, wood and furniture sectors earn 25% less. For unskilled workers the variation between sectors is generally lower, with the only significant sectoral effects being for workers in the machinery sector, who earn 28% less, and those in the furniture sector, who earn 16% less. Firm age, union status, state ownership and foreign ownership have no significant effect, and workers in the Cape Coast and Takoradi earn less than those in Accra or Kumasi. A one standard error change in firm fixed effects will result in a 1% change in wages, while capital:labour ratios do not have a significant effect.

Technology-Return to Education Nexus

Another question arising from the firm level work is “are firms which produce differently seeing a different return to skills?” Caselli and Coleman [2006] propose a technology frontier where countries differ in the efficiency with which they use skilled and unskilled labour. There is a tradeoff between the two, such that using skilled labour more efficiently entails using unskilled labour less efficiently. We can undertake a similar exercise with the firm data. Ignoring any possible endogeneity problem (as we are not concerned about the point estimates) we run an earnings function (ie Equation 4.21) for skilled and unskilled workers separately, including a firm fixed effect, and extract this firm level fixed effect for each skill type. This gives us two fixed effects for each firm. One of these represents the firm specific increment (which may be negative) that skilled workers receive in their wages from being in the specific firm, as opposed to the average firm, while the other is the corresponding effect for the unskilled. Assuming that wages reflect productivity within the firm then we can link the firm fixed effect from the individual earnings function to the effectiveness with which firms can use workers of different types.

The fixed effects from these two regressions are plotted against one another in Figure 4.5. We see that firms which are more effective at utilising skilled labour are also more effective at utilising unskilled labour. In fact, it is not possible to reject the null hypothesis that, for a regression line drawn through these points, the constant term is zero and the slope is one. A unit increase in the skilled fixed effect is associated with a unit increase in the

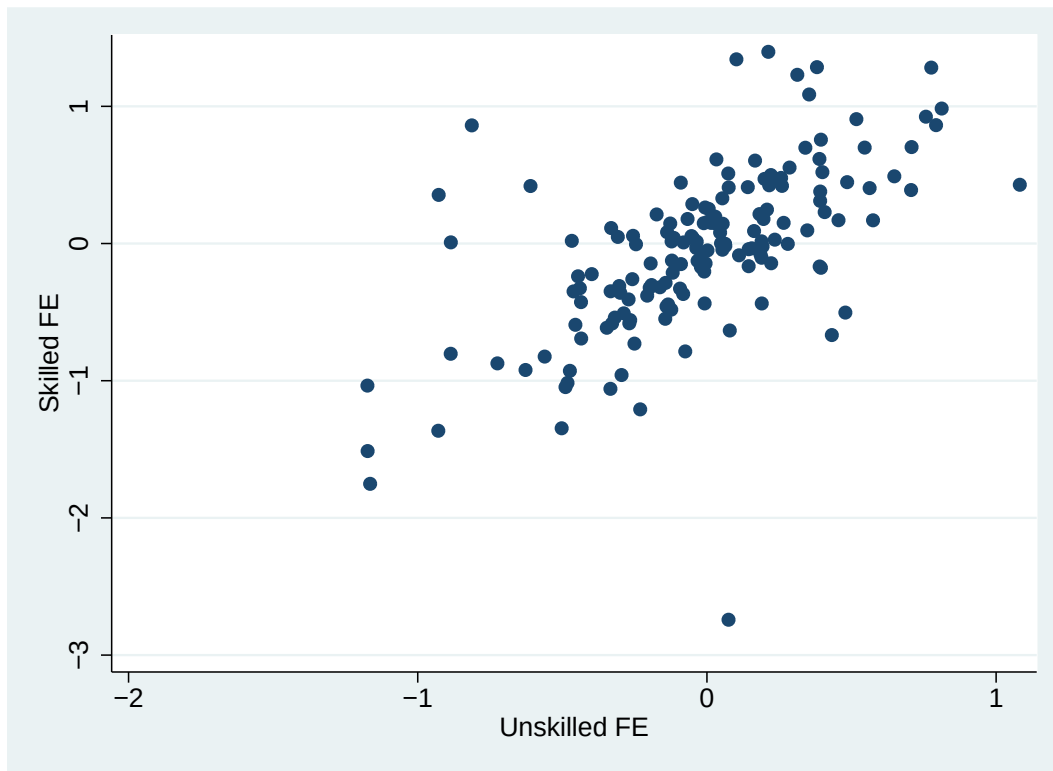


Figure 4.5: Firm fixed effects extracted from worker level earnings functions conducted by skill classification of worker. These fixed effects were extracted from a fixed-effects earnings function for workers of each skill type, and represent the firm effect on wages where this effect is allowed to be different for skilled and unskilled workers.

unskilled fixed effect. Thus, while there is firm heterogeneity in the magnitude of the fixed effect, the relative efficiency with which skilled and unskilled labour is used is constant across firms, consistent with a homogenous technology. Unlike the findings of Caselli and Coleman at the country level, there is no evidence that firms within a country face such a tradeoff.

Conclusions

So, in summary, what have these earnings functions taught us about how education affects the earnings of Ghanaian workers? The return to the first

ten years of education is low for all workers. Years of education acquired beyond ten years rapidly increase the probability of being selected into a skilled occupation and, for skilled workers only, increase earnings by approximately 10% a year. For those who continue beyond ten years but are not successful in getting a skilled job, the extra education has little effect on their wages. We do not have information on the performance of workers for each year of education, only whether they completed it. But, if we assume that those with better observable outcomes (eg exam results) from post-compulsory education are those who get the skilled jobs, then it appears that post-compulsory education is effective at identifying those individuals who will be more productive to firms and that, for those workers only, the skills learnt in further education are useful.

We can see from Figures 4.3, 4.1 and 4.2 that the earnings premium for a skilled job increases with the number of years of post-compulsory education. For ten years of education, the point where the return to skilled workers begins to rise, the skill premium is 50%¹⁶ and it then increases by approximately 10% for each further year of education. For a worker with thirteen years of education, for example, expected earnings for a skilled worker is around 100% higher than that for an unskilled worker.¹⁷ This gap corresponds precisely with that suggested by the raw data (recall the multiple of two, i.e. 100%, discussed in Section 4.4). Compulsory education does not appear to be assisting the earnings outcomes for any workers, and post-compulsory is useful

¹⁶ $(e^{10.4} - e^{10})/e^{10} \approx 0.50$.

¹⁷A skilled worker with 10 years of education will earn 50% then more than a similarly educated unskilled worker and then receives an additional premium of 10% for each additional year. Thus, compared to the wage of such an unskilled worker, the wage of a skilled worker with 13 years of education would be $1.5(1.1)^3 = 2.00$ times higher.

only if you end up getting a skilled job. For workers with post-compulsory education in unskilled occupations there is a very limited increase in expected wages. For the vast majority of Ghanaian workers we cannot say that years of schooling is a substantial causal source of increased earnings.

4.6 Wage and Productivity Premiums

The earnings and production functions estimated using the matched firm-worker data set can be used to compare the return to human capital received by firms and workers. If labour markets are operating efficiently, then the wage premium earned by workers for acquiring human capital should equal the productivity effect to the firm. Van Biesebroeck [2007] uses another matched data set to document the impact of human capital on firm productivity and earnings in Zimbabwe, Kenya and Tanzania. He finds that human capital has differential effects that are systematically related to the level of development. In Zimbabwe, the most developed of the three at the time of the survey, remuneration reflects the productivity effect of human capital. In Kenya and Tanzania the wage premium for experience and schooling exceeds the productivity premium, while the reverse is true for tenure and training despite the latter two having a strong productivity effect.

We find that the return to tenure is approximately 1% in both the earnings and production functions (see Columns 1-3 of Table 4.13 and Column 3 of Table 4.6).¹⁸ The return to experience, which we proxy for using age,

¹⁸Age and tenure were not included in Table 4.8 because these variables are unavailable for South Korea. If they are included for Ghana, the estimate on age is virtually identical with that in Column 3 of Table 4.6 while that on tenure is lower and insignificant. Note

averages out at between 1.9% and 2.3% in the earnings function but is virtually zero in the production function. Recall that Tables 2.2 and 4.8 show a very low productivity effect of education at the firm level. The earnings functions in Table 4.9 show that unskilled workers receive only low (1-4%), but positive, increments in earnings due to additional schooling, while skilled workers receive a zero return for compulsory education but 10% thereafter. Thus the evidence in this thesis suggests that tenure is appropriately rewarded, but wage premiums for age (experience) and schooling are greater than their productivity effect.

The finding that the individual return to education is only high for relatively educated skilled workers is consistent with skilled labour being complementary with more sophisticated technology. This effect was not identified in any of the production function analysis; however, the inherent use of firm level average education will mask the impact of a small number of highly skilled workers. This is particularly so if there are only a small number of firms with sophisticated elements in their production process. Thus this hypothesis is also consistent with the lack of productivity effects from firm level average education in any of our production functions for Ghana.

4.7 Concluding Remarks

The way in which firms in Ghana and South Korea use skills is a major explanation for relative firm performance. In this chapter we sought to generalise our treatment of employment and education to more precisely identify that possible endogeneity of these variables is not addressed.

the manner in which these elements affect the production of Ghanaian firms. The results from this Chapter show that, even conditioning on the different skill composition of the workforce, Ghanaian firms use skills in a less productive way than South Korean firms. Adjusting the measure of labour input with occupation and education is not enough to account for this difference: the different coefficients in the production function still remain the key. While the Cobb-Douglas specification could not be rejected, the low return to the firm persisted when a CES production function was used to allow for imperfect substitutability between skilled and unskilled labour.

Consideration of the possible endogeneity of education in the earnings function and the impact of a wide range of firm controls led to the conclusion that the return to compulsory education is very low for all workers. Post-compulsory education has no causal impact upon the earnings of those in unskilled occupations, but does raise the earnings of skilled workers by approximately 10% for each additional year over the 10th year. For those workers who have ten years of schooling or less, the earnings premium for being in a skilled occupation is 50%. For the majority of workers selection into occupations is a more important determinant of wages than education. We can be more certain that this is a sorting rather than a productivity effect because, at the firm level, neither the education of skilled nor unskilled workers has a substantial impact upon the output of firms.

That a significant return to education is received only by the small proportion of workers who are both skilled and have post-compulsory education is consistent with this type of skilled labour being complementary to elements of more sophisticated production techniques. The lack of sophistication of

the production technology used by most firms in Ghana is why the return to education is so low.

4.A Unabridged Earnings Functions

	All OLS	Skilled OLS	Unskilled OLS	Skilled Heckman	Unskilled Heckman
	1	2	3	4	5
Educ	-0.0473*** (0.0102)	-0.0875*** (0.0184)	-0.0102 (0.0099)	-0.4223* (0.1691)	0.1788* (0.0840)
Educ ²	0.0057*** (0.0006)	0.0067*** (0.0009)	0.0017** (0.0006)	0.0187** (0.0060)	-0.0047 (0.0060)
Age	0.0565*** (0.0070)	0.0643*** (0.0125)	0.0522*** (0.0066)	0.0501* (0.0237)	0.0343* (0.0141)
Age ²	-0.0005*** (0.0001)	-0.0006*** (0.0001)	-0.0005*** (0.0001)	-0.0005* (0.0002)	-0.0001 (0.0002)
Tenure	0.0095* (0.0043)	0.0014 (0.0071)	0.0120** (0.0045)	0.0153 (0.0108)	0.0122 (0.0093)
Tenure ²	0.0000 (0.0001)	0.0002 (0.0002)	-0.0001 (0.0002)	-0.0002 (0.0003)	-0.0001 (0.0003)
EduWgt	0.0270 (0.0156)	0.0633** (0.0210)	0.0185 (0.0178)	0.1039* (0.0487)	-0.0074 (0.0248)
ΔEduWgt	-0.0118 (0.0076)	-0.0131 (0.0111)	0.0030 (0.0103)	-0.0171 (0.0202)	-0.0065 (0.0145)
AgeWgt	-0.0184** (0.0064)	0.0006 (0.0081)	-0.0275*** (0.0066)	0.0167 (0.0144)	-0.0511*** (0.0079)
ΔAgeWgt	-0.0015 (0.0033)	-0.0031 (0.0049)	0.0011 (0.0043)	-0.0082 (0.0076)	-0.0024 (0.0063)
TenWgt	-0.0048 (0.0111)	-0.0265* (0.0131)	0.0136 (0.0118)	-0.0300 (0.0197)	0.0431*** (0.0124)
ΔTenWgt	-0.0128** (0.0042)	-0.0090 (0.0071)	-0.0172** (0.0053)	-0.0099 (0.0160)	-0.0132 (0.0090)
Firm Age	-0.0080 (0.0049)	0.0010 (0.0059)	-0.0155** (0.0050)	-0.0035 (0.0104)	-0.0276*** (0.0070)
FirmAge ²	0.0001 (0.0001)	-0.0000 (0.0001)	0.0002** (0.0001)	0.0000 (0.0002)	0.0003** (0.0001)
InvMills				-0.1338 (0.1796)	-0.2747 (0.1551)
Reset	0.0000	0.0000	0.1003		
Sargan p				0.0783	0.3691
CraggDonald				1.2392	2.4781
Anderson				0.1385	0.0006
Obs	6634	2437	4197	744	1226

Table 4.13: The dependent variable is log of real earnings in 1991 Cedis. These results continue in Tables 4.14 and 4.15.

	All OLS	Skilled OLS	Unskilled OLS	Skilled Heckman	Unskilled Heckman
	1	2	3	4	5
Micro	-0.5211** (0.1946)	-0.0030 (0.4708)	-0.5339** (0.1665)	-1.1135 (0.8138)	-0.2867 (0.2492)
ΔMicro	0.0564 (0.2927)	-0.1641 (0.3964)	0.0916 (0.2874)	-0.4680 (0.8664)	0.4522 (0.3941)
Small	-0.2649** (0.0809)	-0.4501*** (0.1273)	-0.1740* (0.0673)	-0.4692** (0.1634)	-0.0469 (0.0878)
ΔSmall	0.2657 (0.2213)	0.0446 (0.2839)	0.2637 (0.2004)	0.3111 (0.4428)	0.2547 (0.3323)
ΔMedium	0.3187 (0.2225)	0.1342 (0.2662)	0.3239 (0.2003)	0.7501 (0.4192)	0.2918 (0.3368)
Large	0.3564*** (0.0686)	0.2806** (0.0871)	0.3374*** (0.0756)	0.3589* (0.1604)	0.4426*** (0.0843)
ΔLarge	0.4009 (0.2338)	0.2442 (0.2747)	0.3906 (0.2107)	0.7185 (0.4355)	0.6500 (0.3848)
Firm FE	0.3414*** (0.0822)	0.3373** (0.1125)	0.3540*** (0.0867)	0.4648** (0.1533)	0.4474*** (0.0977)
$\ln \frac{K}{L}$	-0.0243 (0.0151)	-0.0101 (0.0212)	-0.0086 (0.0152)	0.0261 (0.0321)	0.0291 (0.0206)
Takoradi	-0.1575 (0.0921)	-0.1915 (0.1221)	-0.2094* (0.0845)	-0.3106* (0.1219)	-0.2859** (0.0911)
Kumasi	0.0384 (0.0540)	0.0578 (0.0909)	-0.0198 (0.0516)	0.0845 (0.1226)	0.1772** (0.0633)
Cape Coast	-0.3770*** (0.0831)	-0.4122** (0.1346)	-0.4261*** (0.0863)	-0.5591 (0.3521)	-0.7559*** (0.1977)
Union	0.0630 (0.0691)	0.1060 (0.1014)	0.0718 (0.0593)	0.0274 (0.1086)	0.0081 (0.0713)
Anyfor	0.0570 (0.0502)	0.0447 (0.0706)	0.0634 (0.0483)	-0.0491 (0.0818)	-0.0204 (0.0621)
State	-0.0902 (0.0731)	-0.0908 (0.0943)	-0.0258 (0.0600)	-0.1198 (0.1448)	0.0715 (0.1129)
Bakery	-0.0594 (0.1055)	0.3108* (0.1382)	-0.1299 (0.1224)	0.5508* (0.2409)	-0.1425 (0.1016)
Food	-0.0789 (0.0845)	-0.0864 (0.1064)	-0.1144 (0.0772)	-0.1685 (0.1089)	0.0840 (0.0939)
Constant	9.3692*** (0.3353)	8.4792*** (0.5325)	9.7235*** (0.3578)	10.0950*** (1.1996)	9.5530*** (0.5096)

Table 4.14: The dependent variable is log of real earnings in 1991 Cedis. These results are a continuation of those in Table 4.13 and continue in Table 4.15.

	All OLS	Skilled OLS	Unskilled OLS	Skilled Heckman	Unskilled Heckman
	1	2	3	4	5
Drink	0.1728 (0.1048)	0.2902* (0.1363)	0.0998 (0.1528)	-0.0489 (0.1968)	-0.1050 (0.1685)
Textile	-0.0469 (0.1206)	0.0706 (0.1459)	-0.1127 (0.1225)	0.1326 (0.1739)	-0.0876 (0.1235)
Garment	-0.1906* (0.0798)	-0.2768* (0.1143)	-0.1195 (0.0777)	-0.2473 (0.1776)	-0.1228 (0.0990)
Wood	-0.2405* (0.0934)	-0.2992* (0.1195)	-0.1547 (0.0888)	-0.3426** (0.1278)	-0.1302 (0.1044)
Furniture	-0.2035** (0.0682)	-0.2611** (0.0934)	-0.1653* (0.0749)	-0.3791*** (0.1098)	-0.3325*** (0.0867)
Machines	-0.2161 (0.1323)	-0.0470 (0.2100)	-0.2791* (0.1241)	-0.0461 (0.1466)	-0.3274** (0.1198)
Chemical	0.1292 (0.0913)	0.1016 (0.1453)	0.0154 (0.0706)	0.0944 (0.1979)	-0.0330 (0.1364)
wave2	0.0231 (0.0518)	0.1506 (0.0814)	-0.0528 (0.0522)		
wave3	0.0510 (0.0523)	0.2043* (0.0832)	-0.0329 (0.0558)		
wave4	0.0359 (0.0528)	0.1406* (0.0667)	-0.0824 (0.0572)		
wave5	-0.0960 (0.0536)	0.0599 (0.0677)	-0.2364*** (0.0580)		
wave6	-0.0360 (0.0541)	0.0973 (0.0691)	-0.1754** (0.0567)		
wave7	0.0091 (0.0542)	0.1659* (0.0694)	-0.1338* (0.0576)		
wave8	0.2160*** (0.0555)	0.2826*** (0.0798)	0.1327* (0.0602)	-0.0223 (0.1245)	-0.0905 (0.0757)
wave9	0.2278*** (0.0580)	0.2959*** (0.0803)	0.1452* (0.0588)	0.0031 (0.1142)	-0.0879 (0.0734)
wave10	0.2251** (0.0738)	0.2348* (0.0968)	0.1563 (0.0838)	-0.1335 (0.1099)	-0.0717 (0.0732)
wave11	0.4258*** (0.0762)	0.3922*** (0.1066)	0.3874*** (0.0827)	0.0103 (0.1037)	0.1314 (0.0695)
wave12	0.3230*** (0.0831)	0.3474** (0.1167)	0.2737** (0.0891)		

Table 4.15: The dependent variable is log of real earnings in 1991 Cedis. These results are a continuation of those in Tables 4.13 and 4.14.

	All OLS	Skilled OLS	Unskilled OLS	Skilled IV 2SLS	Unskilled IV 2SLS
	1	2	3	4	5
Educ	-0.0533** (0.0176)	-0.0731* (0.0286)	-0.0002 (0.0206)	-0.3644* (0.1502)	0.3023** (0.0959)
Educ ²	0.0058*** (0.0010)	0.0062*** (0.0015)	0.0006 (0.0012)	0.0171** (0.0058)	-0.0140* (0.0064)
Age	0.0490*** (0.0127)	0.0613* (0.0263)	0.0543*** (0.0118)	0.0620*** (0.0182)	0.0241 (0.0145)
Age ²	-0.0004** (0.0001)	-0.0006* (0.0003)	-0.0005** (0.0001)	-0.0006** (0.0002)	-0.0000 (0.0002)
Tenure	0.0133 (0.0087)	0.0109 (0.0149)	0.0098 (0.0091)	0.0141 (0.0105)	0.0082 (0.0097)
Tenure ²	-0.0002 (0.0002)	-0.0001 (0.0003)	-0.0002 (0.0003)	-0.0002 (0.0003)	0.0000 (0.0003)
EduWgt	0.0639** (0.0231)	0.0582 (0.0386)	0.0714* (0.0273)	0.0903* (0.0403)	-0.0055 (0.0252)
ΔEduWgt	-0.0151 (0.0168)	-0.0207 (0.0201)	-0.0009 (0.0204)	-0.0161 (0.0195)	0.0046 (0.0149)
AgeWgt	-0.0310*** (0.0087)	0.0048 (0.0160)	-0.0552*** (0.0096)	0.0128 (0.0124)	-0.0524*** (0.0082)
ΔAgeWgt	-0.0046 (0.0078)	-0.0085 (0.0141)	-0.0083 (0.0077)	-0.0081 (0.0074)	-0.0019 (0.0067)
TenWgt	0.0213 (0.0145)	-0.0187 (0.0229)	0.0539** (0.0176)	-0.0300 (0.0190)	0.0466*** (0.0128)
ΔTenWgt	-0.0143 (0.0099)	-0.0203 (0.0194)	-0.0092 (0.0113)	-0.0101 (0.0155)	-0.0128 (0.0094)
Firm Age	-0.0265*** (0.0064)	-0.0009 (0.0119)	-0.0309*** (0.0071)	-0.0042 (0.0099)	-0.0235** (0.0074)
FirmAge ²	0.0004*** (0.0001)	0.0000 (0.0002)	0.0004*** (0.0001)	0.0001 (0.0001)	0.0002* (0.0001)
Reset	0.0205	0.0033	0.6635		
Sargan p				0.0671	0.7132
CraggDonald				2.1030	2.4819
Anderson				0.0032	0.0006
Obs	1970	744	1226	744	1226

Table 4.16: The dependent variable is log of real earnings in 1991 Cedis. Columns 1-3 present OLS estimates for the sample for which our instruments are available, while Columns 4 and 5 present the 2SLS IV estimates when education is instrumented with distance from school, parents education and parents occupation. These results are continued in Tables 4.17 and 4.18.

	All OLS	Skilled OLS	Unskilled OLS	Skilled IV 2SLS	Unskilled IV 2SLS
	1	2	3	4	5
Micro	-0.3384 (0.2079)	-1.6454*** (0.4506)	-0.1320 (0.2530)	-1.2335 (0.7641)	-0.2970 (0.2623)
Δ Micro	0.6647 (0.3819)	-0.0748 (0.8759)	0.4538 (0.3757)	-0.4173 (0.8415)	0.5847 (0.4153)
Small	-0.1992 (0.1253)	-0.4757* (0.2142)	-0.1078 (0.1230)	-0.4758** (0.1573)	-0.0554 (0.0917)
Δ Small	0.5215 (0.3682)	0.6332 (0.5667)	0.2122 (0.3693)	0.3852 (0.4250)	0.3768 (0.3510)
Δ Medium	0.6260 (0.3652)	1.0147 (0.5244)	0.2750 (0.3718)	0.8073* (0.4058)	0.4355 (0.3554)
Large	0.4952*** (0.0938)	0.2189 (0.1452)	0.5271*** (0.1201)	0.3137* (0.1356)	0.4005*** (0.0902)
Δ Large	0.9331* (0.3734)	1.0793* (0.5185)	0.6916 (0.3952)	0.7993 (0.4150)	0.9015* (0.4031)
Firm FE	0.4132*** (0.1115)	0.4263* (0.1907)	0.4041** (0.1212)	0.4493** (0.1456)	0.4799*** (0.1030)
$\ln \frac{K}{L}$	-0.0111 (0.0234)	0.0203 (0.0411)	0.0048 (0.0258)	0.0248 (0.0311)	0.0358 (0.0219)
Takoradi	-0.1949* (0.0967)	-0.1757 (0.1562)	-0.3675*** (0.1064)	-0.2909* (0.1174)	-0.2622** (0.0967)
Kumasi	0.2111** (0.0767)	0.1456 (0.1555)	0.1404 (0.0729)	0.0660 (0.1135)	0.1488* (0.0661)
Cape Coast	-0.4448*** (0.1120)	-0.4249 (0.2742)	-0.6794*** (0.1069)	-0.4447 (0.2758)	-0.9734*** (0.1994)
Union	0.0032 (0.1190)	0.0538 (0.1585)	0.0125 (0.1263)	0.0433 (0.1043)	-0.0142 (0.0745)
Anyfor	0.0249 (0.0641)	-0.0848 (0.1173)	0.0284 (0.0775)	-0.0582 (0.0781)	-0.0084 (0.0645)
State	-0.0913 (0.1523)	0.0456 (0.1458)	-0.0742 (0.1854)	-0.0834 (0.1312)	0.1855 (0.1223)
Constant	9.6651*** (0.5143)	8.2496*** (1.1376)	9.8998*** (0.5409)	9.5107*** (1.0215)	9.2720*** (0.5313)

Table 4.17: The dependent variable is log of real earnings in 1991 Cedis. Columns 1-3 present OLS estimates for the sample for which our instruments are available, while Columns 4 and 5 present the 2SLS IV estimates when education is instrumented with distance from school, parents education and parents occupation. These results are a continuation of those in Table 4.16 and are continued in Table 4.18.

	All OLS	Skilled OLS	Unskilled OLS	Skilled IV 2SLS	Unskilled IV 2SLS
	1	2	3	4	5
Bakery	-0.0320 (0.1485)	0.4691* (0.1898)	-0.1136 (0.1497)	0.5653* (0.2309)	-0.2147* (0.1055)
Food	-0.0686 (0.1251)	-0.1087 (0.1532)	-0.0950 (0.1324)	-0.1664 (0.1057)	0.1534 (0.1030)
Drink	-0.1392 (0.1626)	-0.0989 (0.2027)	-0.1011 (0.2433)	-0.0668 (0.1891)	-0.0388 (0.1761)
Textile	-0.0855 (0.1687)	0.0476 (0.2345)	-0.2166 (0.1711)	0.1295 (0.1689)	-0.1814 (0.1228)
Garment	-0.1637 (0.1170)	-0.3199 (0.2086)	-0.1422 (0.1283)	-0.2640 (0.1694)	-0.2025* (0.1021)
Wood	-0.2764* (0.1228)	-0.4322** (0.1568)	-0.0775 (0.1448)	-0.3466** (0.1242)	-0.1528 (0.1104)
Furniture	-0.2744* (0.1056)	-0.3768* (0.1526)	-0.3193* (0.1270)	-0.3683*** (0.1037)	-0.4067*** (0.0903)
Machines	-0.2008 (0.1911)	-0.1160 (0.2446)	-0.3625 (0.2405)	-0.0649 (0.1387)	-0.3239* (0.1260)
Chemical	0.0581 (0.1620)	-0.0683 (0.2479)	-0.0781 (0.1498)	0.0389 (0.1731)	-0.1348 (0.1400)
wave9	0.0270 (0.0278)	0.0285 (0.0398)	0.0197 (0.0287)	0.0216 (0.0620)	0.0075 (0.0495)
wave10	0.0288 (0.0706)	-0.0388 (0.0973)	0.0143 (0.0861)	-0.0947 (0.1009)	-0.0114 (0.0698)
wave11	0.2290*** (0.0634)	0.1339 (0.1002)	0.2276** (0.0771)	0.0507 (0.1113)	0.1969** (0.0738)
wave12	0.1366 (0.0775)	0.1054 (0.1042)	0.1137 (0.0942)	0.0321 (0.1214)	0.0744 (0.0799)

Table 4.18: The dependent variable is log of real earnings in 1991 Cedis. Columns 1-3 present OLS estimates for the sample for which our instruments are available, while Columns 4 and 5 present the 2SLS IV estimates when education is instrumented with distance from school, parents education and parents occupation. These results are a continuation of those in Tables 4.16 and 4.17.

Chapter 5

Conclusions

The low return to education and the much lower level of value added per worker in Ghanaian manufacturing firms is inextricably linked to the production technology of firms. Technological heterogeneity is a major explanatory factor in understanding cross-country variations in wages and firm productivity at the micro level.

Chapter 2 showed that output per worker differentials between Ghanaian and South Korean firms result from a difference in production technology and a difference in the firm level return 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. Despite this difference in technology a value added regression at the micro level implies that the value added coefficients across the countries are similar. The number of years of schooling

received by workers in manufacturing firms in the two countries is similar, but the return to education experienced by the firm is very weak and convex in Ghana and strong and concave in South Korea. The average return is 10.8% in South Korea and 2.6% in Ghana.

A similar pattern is observed within Africa, with the cross-country pattern of technology identified in this thesis summarised in Figure 5.1. Table 3.2 presents Cobb-Douglas production functions for the five African countries in our data set. 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. Even within a single sector, firms across countries can use different technologies. Human capital was not available for South Africa or Nigeria; however, for those countries for which it was available, Chapter 3 confirms 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 data produces the surprising result that TFP differences can be completely explained at the micro level by differences in the return to education and the way in which inputs are used (i.e. technology). 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. This is consistent with our finding that the return on skills is much lower in poorer economies. Our results are indicative that one reason why the extensive policy focus on improving human capital in developing countries has not led to major gains in incomes is the lack of investment in capital and inappropriate production techniques.

Note the pattern relating income to technology in Figure 5.1. 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 return to worker education is low. Rising incomes are associated with an increased return to education and a

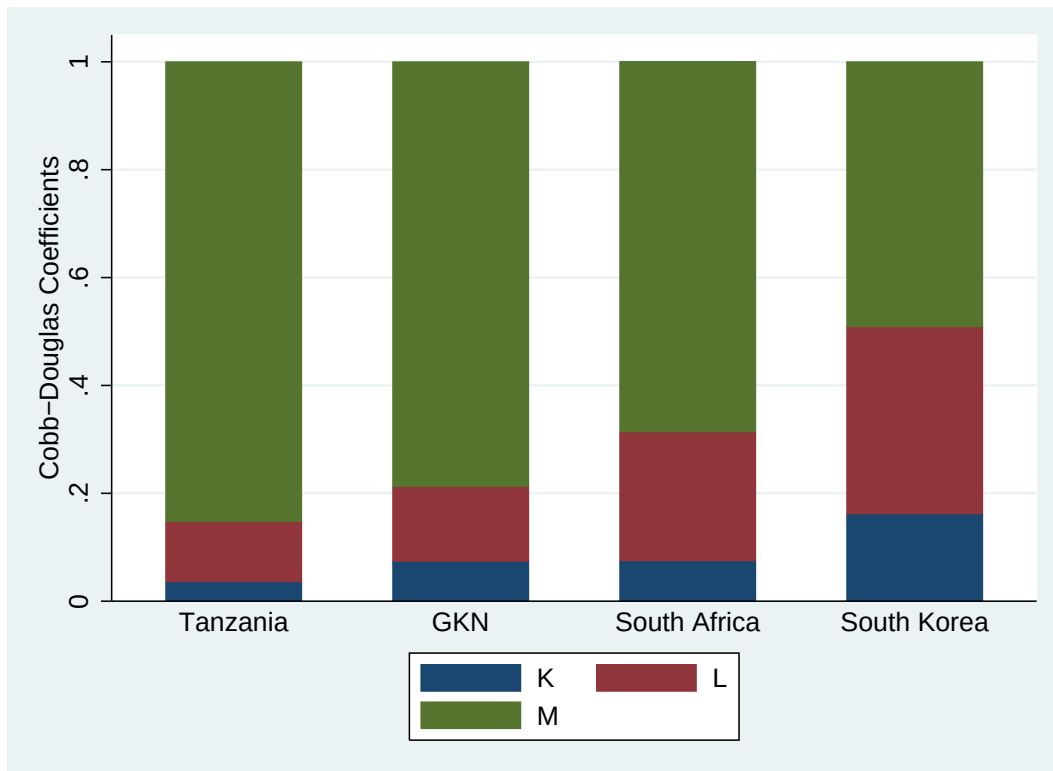


Figure 5.1: Chart summarising the information on technology contained in Tables 2.2 and 3.2. The output elasticities for materials and indirect costs have been combined.

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.

Poverty reduction through productive activities occurs mainly through the channel of wages. The wages that a firm pays will be dependent upon the extra output that an extra worker will be able to produce (the marginal

product) and the cost of the other inputs (capital, materials etc) required to enable that worker to produce. The technology used by Ghanaian firms has a lower marginal product of labour than that used by South Korean firms, in part due to the lower rate of return to education, and so firms using that technology will pay lower wages.

Chapter 4 showed that, even allowing for the different skill composition and years of schooling of the workforce, Ghanaian firms use skills in a less productive way than South Korean firms. For workers and firms in Ghana, education appears to be mostly a sorting device. Conditional upon selection into occupations, the only group of workers for whom education appreciably increases earnings are those employed in skilled jobs with more than ten years of education. The skill premia after compulsory schooling is approximately 50%, and increases by 10% for every further year of education. The impact of education on earnings and occupation is relatively small, and many Ghanaian workers would increase their discounted lifetime earnings by leaving education earlier than they do now. In order to give workers the incentives to acquire substantial human capital the technology being used by Ghanaian firms will need to change. Any complementarities between skilled labour and sophisticated technologies would imply that this would need to be a joint process. The choice of technology in Ghana is labour intensive because wages are low and high quality human capital scarce. However, the marginal product of a worker is low because of the choice of technology.

Production technology is a vital link in ensuring that human capital can be used effectively. It is not enough for workers simply to acquire more years of schooling. The rate of return can be increased partly through improving

the quality of education but, no matter how good an education Ghanaian workers receive, they will not be compensated well unless the rate of return that firms receive from their education increases. For this to happen, Ghanaian firms need to fundamentally change the way in which they use inputs. The issues underlying such a technology switch are numerous and complicated. Firms need access to large markets so they can achieve the scale economies required to justify the fixed-cost investment in more capital intensive production techniques. African Governments need to ensure that exports are a focus of domestic industrial policy and that firms are not discouraged through perverse financial incentives, poor infrastructure or regulations. The investment climate must also be improved. This will have the effect of reducing risk levels, which our model of technology choice suggests may further enhance the likelihood of a technological transition. Ultimately, it is this investment by firms that will increase the return to education and raise incomes and output.

The empirical results of all chapters are consistent with the model of the world technology frontier given by Equation 3.1. True production technology is a gross output constant returns to scale production function with a fixed relativity between the output elasticities of capital and labour which, in turn, leads to the apparent homogeneity of the value added production function. The process by which manufacturing sectors can be transformed from low to high productivity activities, with the corresponding increases in wages and the return on capital, is one whereby the share of intermediate inputs in production is reduced.

Many countries, but particularly those in East Asia, have lifted much of

their population out of poverty by harnessing the power of productive activities and industrial development. Firms are the ultimate source of output, productivity and wages in an economy and this thesis argues that the manner in which African firms differ from those in South Korea is fundamental to understanding the development process. The return to education is much lower in Africa, and the technology they use is much more heavily reliant upon the use of raw materials. African firms need to make a technological transition and the return to education must be increased. Transformation and growth at the firm level provides Africa's best chance to lift its people out of poverty for the long term.

Bibliography

- [Abel and Eberly, 1999] Abel, A. and Eberly, J. (1999). The effects of irreversibility and uncertainty on capital accumulation. *Journal of Monetary Economics*, 44:339–377.
- [Acemoglu, 1996] Acemoglu, D. (1996). A Microfoundation for Social Increasing Returns in Human Capital Accumulation. *Quarterly Journal of Economics*, 111(3):779–804.
- [Acemoglu and Angrist, 1999] Acemoglu, D. and Angrist, J. (1999). How Large Are Human-Capital Externalities? Evidence from Compulsory Schooling Laws. *NBER Working Paper*, 7444.
- [Akerberg et al., 2005] Akerberg, D. A., Caves, K., and Frazer, G. (2005). Structural Identification of Prediction Functions. UCLA Working Paper.
- [Aghion and Howitt, 1998] Aghion, P. and Howitt, P. (1998). *Endogenous Growth Theory*. MIT Press.
- [Allen, 1967] Allen, R. G. D. (1967). *Mathematical Analysis for Economists*. Macmillan and Company Limited, London.

- [Apergis, 2007] Apergis, N. (April 2007). Old Wine in a New Bottle: Are Financial Variables Omitted Variables in the Production Function? *Working Paper*, University of Piraeus.
- [Arellano and Bond, 1991] Arellano, M. and 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.
- [Arellano and Bover, 1995] Arellano, M. and Bover, O. (1995). Another look at the Instrumental Variable Estimation of Error-components Models. *Journal of Econometrics*, 68:29–51.
- [Aw and Hwang, 1995] Aw, B. and Hwang, A. (1995). Productivity and the Export Market: A Firm-level Analysis. *Journal of Development Economics*, 47:313–332.
- [Basu and Fernald, 1995] Basu, S. and Fernald, J. G. (1995). Are apparent productive spillovers a figment of specification error? *Journal of Monetary Economics*, 36:165–188.
- [Basu and Weil, 1998] Basu, S. and Weil, D. N. (1998). Appropriate Technology and Growth. *The Quarterly Journal of Economics*, 113(4):1025–1054.
- [Beattie and Taylor, 1985] Beattie, B. and Taylor, C. (1985). *The Economics of Production*, chapter 6. John Wiley and Sons, New York.
- [Behar, 2007] Behar, A. (2007). *Are Skilled and Unskilled Labour Complements or Substitutes?* PhD thesis, Department of Economics, University of Oxford.

- [Biesebroeck, 2007] Biesebroeck, J. V. (2007). Wage and productivity Premiums in Sub-Saharan Africa. *NBER Working Paper No. W13306*.
- [Bigsten et al., 2000] Bigsten, A., Collier, P., Dercon, S., Fafchamps, M., Appleton, S., Gauthier, B., Gunning, J. W., Isaksson, A., Oduro, A., Oostendorp, R., Pattillo, C., Söderbom, M., Teal, F., and Zeufack, A. (2000). Rates of Return on Physical and Human Capital in Africa's Manufacturing Sector. *Economic Development and Cultural Change*, 48(4):801–827.
- [Bigsten et al., 2003] Bigsten, A., Collier, P., Dercon, S., Fafchamps, M., Gauthier, B., Gunning, J. W., Oduro, A., Oostendorp, R., Pattillo, C., Söderbom, M., Teal, F., and Zeufack, A. (2003). Credit Constraints in Manufacturing Enterprises in Africa. *Journal of African Economies*, 12(1).
- [Bigsten et al., 2004] Bigsten, A., Collier, P., Dercon, S., Fafchamps, M., Gauthier, B., Gunning, J. W., Oduro, A., Oostendorp, R., Pattillo, C., Söderbom, M., Teal, F., and Zeufack, A. (2004). Do African Manufacturing Firms Learn from Exporting? *The Journal of Development Studies*, 40(3):115–141.
- [Bigsten and Söderbom, 2005] Bigsten, A. and Söderbom, M. (2005). What Have We Learned From a Decade of Manufacturing Enterprise Surveys in Africa? *World Bank Policy Research Working Paper*, 3798.
- [Bils and Klenow, 2000] Bils, M. and Klenow, P. (2000). Does Schooling Cause Growth. *American Economic Review*, 90(5):1160–1183.
- [Blackorby and Russell, 1981] Blackorby, C. and Russell, R. R. (1981). The Morishima Elasticity of Substitution; Symmetry, Constancy, Separability,

- and its Relationship to the Hicks and Allen Elasticities. *Review of Economic Studies*, 48:147–58.
- [Blackorby and Russell, 1989] Blackorby, C. and Russell, R. R. (1989). Will the Real Elasticity of Substitution Please Stand Up? (A Comparison of the Allen/Uzawa and Morishima Elasticities). *The American Economic Review*, 79(4):882–888.
- [Bleaney, 1996] Bleaney, M. F. (1996). Macroeconomic Stability, Investment and Growth in Developing Countries. *Journal of Development Economics*, 48:461–477.
- [Blundell and Bond, 1998] Blundell, R. and Bond, S. (1998). Initial Conditions and Moment Restrictions in Dynamic Panel Data Models. *Journal of Econometrics*, 87:115–143.
- [Blundell and Bond, 2000] Blundell, R. and Bond, S. (2000). GMM Estimation with Persistent Panel Data: an Application to Production Functions. *Econometric Reviews*, 19:321–340.
- [Boissiere et al., 1985] Boissiere, M., Knight, J. B., and Sabot, R. H. (1985). Earnings, Schooling, Ability, and Cognitive Skills. *The American Economic Review*, 75(5):1016–1030.
- [Bond and Söderbom, 2005] Bond, S. and Söderbom, M. (2005). Adjustment Costs and the Identification of Cobb-Douglas Production Functions. *The Institute for Fiscal Studies Working Paper Series*, WP05/04.

- [Bowsher, 2002] Bowsher, C. G. (2002). On testing overidentifying restrictions in dynamic panel data models. *Economics Letters*, 77:211–220.
- [Campbell and Jennings, 1990] Campbell, H. F. and Jennings, S. M. (1990). Technology and Input Demand in the Tasmanian Sawmilling Industry. *Australian Economic Papers*, 29(55):272–282.
- [Card, 1999] Card, D. (1999). The Causal Effect of Education on Earnings. In Ashenfelter, O. and Card, D., editors, *Handbook of Labour Economics*, pages 1801–1863. Elsevier Science.
- [Card, 2001] Card, D. (2001). Estimating the Return to Schooling: Progress on Some Persistent Econometric Problems. *Econometrica*, 69(5):1127–1160.
- [Card and DiNardo, 2002] Card, D. and DiNardo, J. (2002). Skill-biased Technological Change and Rising Wage Inequality: Some Problems and Puzzles. *Journal of Labour Economics*, 20(4):733–783.
- [Caselli, 2005] Caselli, F. (2005). Accounting for Crosss-Country Income Differences. In Aghion, P. and Durlauf, S., editors, *Handbook of Economic Growth*, pages 679–741. Elsevier.
- [Caselli and Coleman, 2006] Caselli, F. and Coleman, II, W. J. (2006). The World Technology Frontier. *American Economic Review*, 96(3).
- [Caselli and Feyrer, 2007] Caselli, F. and Feyrer, J. (May 2007). The Marginal Product of Capital. *Quarterly Journal of Economics*, 122(2):535–568.

- [Chen and Tang, 1987] Chen, T. and 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.
- [Clark, 2007] Clark, G. (2007). *A Farewell to Alms*. Princeton University Press.
- [Clerides et al., 1998] Clerides, S., Lach, S., and Tybout, J. (1998). Is Learning by Exporting Important? Micro-dynamic Evidence from Colombia, Mexico and Morocco. *Quarterly Journal of Economics*, 113:903–947.
- [Davis et al., 1996] Davis, S. J., Haltiwanger, J. C., and Schuh, S. (1996). *Job Creation and Destruction*. The MIT Press, Cambridge MA.
- [Deardorff, 2001] Deardorff, A. V. (2001). Rich and Poor Countries in Neoclassical Trade and Growth. *The Economic Journal*, 111:277–294.
- [Duraismy, 2002] Duraismy, P. (2002). Changes in Returns to Education in India, 1983-94: by Gender, Age-Cohort and Location. *Economics of Education Review*, 21:609–622.
- [Durlauf et al., 2005] Durlauf, S., Johnson, P., and Temple, J. (2005). Growth Econometrics. In Aghion, P. and Durlauf, S., editors, *Handbook of Economic Growth Vol 1*, pages 555–677. Elsevier.
- [Easterly and Levine, 2001] Easterly, W. and Levine, R. (March 2001). It’s Not Factor Accumulation: Stylized Facts and Growth Models. *The World Bank Economic Review*, 15(2):177–219.

- [Eifert et al., 2005] Eifert, B., Gelb, A., and Ramachandran, V. (2005). Business Environment and Comparative Advantage in Africa: Evidence from the Investment Climate Data. *Center for Global Development Working Paper*, 56.
- [Elberfeld and Götz, 2002] Elberfeld, W. and Götz, G. (2002). Market Size, Technology Choice, and Market Structure. *German Economic Review*, 3(1):25–41.
- [Escribano and Guasch, 2005] Escribano, A. and Guasch, J. (2005). Assessing the Impact of the Investment Climate on Productivity Using Firm-Level Data: Methodology and the Cases of Guatemala, Honduras and Nicaragua. *World Bank Policy Research Working Papers*, 3621.
- [Ethier, 1982] Ethier, W. J. (1982). National and International Returns to Scale in the Modern Theory of International Trade. *American Economic Review*, 72(3):389–405.
- [Fafchamps et al., 2000] Fafchamps, M., Gunning, J., and Oostendorp, R. (2000). Inventories and Risk in African Manufacturing. *The Economic Journal*, 110(466):861.
- [Grossman and Helpman, 1995] Grossman, G. M. and Helpman, E. (1995). Technology and Trade. In Grossman, G. M. and Rogoff, K., editors, *Handbook of International Economics. Volume 3*, pages 1279–1337. Elsevier.
- [Habyarimana, 2003] Habyarimana, J. (2003). The Benefits of Banking Relationships: Evidence from Uganda’s Banking Crisis. mimeo, Harvard University.

- [Hall and Jones, 1999] Hall, R. E. and Jones, C. I. (1999). Why Do Some Countries Produce So Much More Output Per Worker Than Others? *Quarterly Journal of Economics*, 114(1):83–116.
- [Hallward-Driemeier, 2001] Hallward-Driemeier, M. (2001). Firm-Level Survey Provides Data on Asia’s Corporate Crisis and Recovery. *World Bank Working Paper Series*, 2515.
- [Hallward-Driemeier et al., 2002] Hallward-Driemeier, M., Iarossi, G., and Sokoloff, K. L. (2002). Exports and Manufacturing Productivity in East Asia: A Comparative Analysis with Firm-Level Data. *NBER Working Paper Series*, 8894.
- [Harrigan, 1999] Harrigan, J. (1999). Estimation of Cross-Country Differences in Industry Production Functions. *Journal of International Economics*, 47:267–293.
- [Hay, 2001] Hay, D. A. (2001). The Post-1990 Brazilian Trade Liberalization and the Performance of Large Manufacturing Firms: Productivity, Market Share and Profits. *The Economic Journal*, 111:620–641.
- [Heckman, 1979] Heckman, J. (1979). Sample Selection Bias as a Specification Error. *Econometrica*, 47(1):153.
- [Heston et al., 2002] Heston, A., Summers, R., and Aten, B. (2002). Penn World Table Version 6.1.
- [Hicks, 1970] Hicks, J. (1970). Elasticity of substitution again: Substitutes and complements. *Oxford Economic Papers*, 22:289–96.

- [Hubbard, 1994] Hubbard, R. G. (1994). Investment Under Uncertainty: Keeping One's Options Open. *Journal of Economic Literature*, 32:1816–1831.
- [Humphrey and Moroney, 1975] Humphrey, D. and Moroney, J. (1975). Substitution among Capital, Labor, and Natural Resource Products in American Manufacturing. *Journal of Political Economy*, 83(1):57–82.
- [Ibarra, 1995] Ibarra, L. A. (1995). Credibility of Trade Policy Reform and Investment: The Mexican Experience. *Journal of Development Economics*, 47:39–60.
- [Jerzmanowski, 2007] Jerzmanowski, M. (2007). Total Factor Productivity Differences: Appropriate Technology vs. Efficiency. *European Economic Review*, 51:2080–2110.
- [Jones, 2005] Jones, C. I. (2005). The Shape of Production Functions and the Direction of Technical Change. *The Quarterly Journal of Economics*, 120(2):517–549.
- [Jones, 2001] Jones, P. (2001). Are Educated Workers Really More Productive? *Journal of Development Economics*, 64:57–79.
- [Jorgenson, 1990] Jorgenson, D. (1990). Productivity and Economic Growth. In Berndt, E. and Triplett, J., editors, *Fifty Years of Economic Measurement*, pages 19–118. University of Chicago Press.

- [Jorgenson et al., 1987] Jorgenson, D., Kuroda, M., and Nishimizu, M. (1987). Japan-US Industry-level Productivity Comparisons, 1960-1985. *Journal of the Japanese and International Economies*, 1:1–30.
- [Kingdon and Unni, 2001] Kingdon, G. and Unni, J. (2001). Education and Women’s Labour Market Outcomes in India. *Education Economics*, 9:173–194.
- [Knight et al., 1992] Knight, J., Sabot, R., and Hovey, D. (1992). Is the Rate of Return on Primary Schooling Really 26 Per Cent? *Journal of African Economies*, 1(2):192.
- [Krueger and Lindahl, 2001] Krueger, A. B. and Lindahl, M. (2001). Education for Growth: Why and For Whom? *Journal of Economic Literature*, 39:1101–1136.
- [Lambson, 1991] Lambson, V. E. (1991). Industry Evolution with Sunk Costs and Uncertain Market Conditions. *International Journal of Industrial Organization*, 9(2):171–196.
- [Lange and Topel, 2006] Lange, F. and Topel, R. (2006). The Social Value of Education and Human Capital. In Hanushek, E. A. and Welch, F., editors, *Handbook of the Economics of Education Volume 1*, pages 459–509. Elsevier.
- [Lucas, 2002] Lucas, R. (2002). *Lectures on Economic Growth*. Harvard University Press.

- [Malik et al., 2006] Malik, A., Teal, F., and Baptist, S. (2006). The Performance of Nigerian Manufacturing Firms: Report on the Nigerian Manufacturing Enterprise Survey 2004. United Nations Industrial Development Organisation Report.
- [Monk et al., 2008] Monk, C., Sandefur, J., and Teal, F. (2008). Does Doing an Apprenticeship Pay Off? Evidence from Ghana. *Centre for the Study of African Economies Worker Paper Series*, 8.
- [Pack, 1993] Pack, H. (1993). Productivity and Industrial Development in Sub-Saharan Africa. *World Development*, 21:1–16.
- [Rankin et al., 2006] Rankin, N., Söderbom, M., and Teal, F. (2006). Exporting from Manufacturing Firms in Sub-Saharan Africa. *Journal of African Economies*, 15(4):671–687.
- [Rankin, 2004] Rankin, N. A. (2004). *The Determinants of Manufacturing Exports from Sub-Saharan Africa*. PhD thesis, Hertford College and the Centre for the Study of African Economies, University of Oxford.
- [Roodman, 2006] Roodman, D. (2006). How to Do xtabond2: An Introduction to “Difference” and “System” GMM in Stata. *Center for Global Development Working Paper*, 106.
- [Servén, 1997] Servén, L. (1997). Irreversibility, Uncertainty and Private Investment: Analytical Issues and Some Lessons for Africa. *World Bank Working Paper Series*, 1722.

- [Söderbom and Teal, 2004] Söderbom, M. and Teal, F. (2004). Size and Efficiency in African Manufacturing Firms: Evidence from Firm-level Panel Data. *Journal of Development Economics*, 73:369–394.
- [Söderbom et al., 2005] Söderbom, M., Teal, F., and Wambugu, A. (2005). Unobserved heterogeneity and the relation between earnings and firm size: evidence from two developing countries. *Economics Letters*, 87(2):153–159.
- [Solow, 1957] Solow, R. (1957). Technical Change and the Aggregate Production Function. *The Review of Economics and Statistics*, 39(3):312–320.
- [Stern, 2004] Stern, D. (2004). Elasticities of Substitution and Complementarity. *Rensselaer Working Papers in Economics*, 0403.
- [Stock and Yogo, 2005] Stock, J. and Yogo, M. (2005). Testing for Weak Instruments in Linear IV Regression. In Andrews, D. and Stock, J., editors, *Identification and Inference for Econometric Models: Essays in Honor of Thomas Rothenberg.*, pages 80–108. Cambridge University Press.
- [Teal, 2000] Teal, F. (2000). Real Wages and Demand for skilled and unskilled male labour in Ghana’s Manufacturing Sector:1991-1995. *Journal of Development Economics*, 61:447–461.
- [Temple, 2005] Temple, J. (2005). Dual Economy Models: A Primer for Growth Economists. *The Manchester School*, 73(4):435–478.
- [Topel, 1999] Topel, R. (1999). Labor Markets and Economic Growth. In Ashenfelter, O. and Card, D., editors, *Handbook of Labour Economics*. Elsevier Science.

- [Topel, 2005] Topel, R. (2005). The Private and Social Values of Education. *Proceedings of the Federal Reserve Bank of Cleveland*, pages 47–57.
- [Tybout et al., 1991] Tybout, J., deMelo, J., and Corbo, V. (1991). The Effects of Trade Reforms on Scale and Technical Efficiency: New Evidence from Chile. *Journal of International Economics*, 31:231–250.
- [Tybout, 2000] Tybout, J. R. (2000). Manufacturing Firms in Developing Countries: How Well Do They Do, and Why? *Journal of Economic Literature*, 38(1):11–44.
- [UNIDO, 2008] UNIDO (2008). United Nations Industrial Development Organisation Industrial Statistics.
- [Uzawa, 1962] Uzawa, H. (1962). Production Functions with Constant Elasticities of Substitution. *Review of Economic Studies*, 29.
- [Varian, 1992] Varian, H. R. (1992). *Microeconomic Analysis 3rd Edition*. W. W. Norton and Company, New York.
- [Young, 1994] Young, A. (April 1994). Lessons from the East Asian NICS: A contrarian view. *European Economic Review*, 38(3-4):964–973.