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ESSAYS ON MANUFACTURING PRODUCTION IN A DEVELOPING ECONOMY: KENYA 1992-94

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Doctoral thesis at Göteborg University:
Essays on manufacturing production in a developing economy: Kenya 1992-94
by Karl Lundvall

Abstract: The dissertation consists of five separate empirical papers based on panel data from Kenyan manufacturing firms in the food, wood, textile and metal sectors, collected during the early 1990s, and an overview of the economic literature on small firms in developing countries. The principal tools of analysis are the microeconomic theory of production and econometrics. Although the main thrust is empirical, the papers may also be of some independent methodological interest.

The first two papers investigate whether technical efficiency is increasing in firm size and age. The evidence supports this claim with respect to firm size, but not age, which is consistent with previous evidence reviewed. These results, obtained using a stochastic frontier production function model in paper 1, are confirmed in paper 2 using data envelopment analysis combined with second-step regression models.

Paper 3 addresses factor intensities and substitution. There exists a positive relationship between firm size and capital intensity. The evidence suggests this is due to non-homothetic technologies and to different input factor prices for small and large firms. Skilled and unskilled workers can be more easily substituted between each other than with capital, which contests the claim that scarcity of skill is a more critical constraint in production than scarcity of capital.

Paper 4 is a broad analysis of the performance of the subsectors in terms of technical efficiency and productivity. Small and informal firms are comparably inefficient. Food, followed by metals, is the most productive sector. Growing firms are more productive than contracting ones, suggesting that high turnover may increase overall sector productivity. Several variables do not explain the variation in productivity, including exporting, credit and foreign ownership. Textiles regressed after the trade liberalisation.

Paper 5 addresses the debate on the usefulness of the informal sector concept by conducting a comparative analysis of formal and informal small firms. Informal firms are younger, less capital-intensive, almost never run by Asians, pay less skilled wages and no taxes, have poor access to credit and have less educated managers. They invest more often and are less efficient than Asian-managed formal firms, but more efficient than those managed by Africans. This suggests that formality status, independent of size, matters. Also important is how ethnicity affects these differences and the graduation of firms from the informal to the formal sectors.

Keywords: Firm size, Kenya, manufacturing, stochastic frontier production functions, data envelopment analysis, technical efficiency, factor substitution, informal sector.

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Abstract

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Pole sana.

An overview

This yellow book is not a comprehensive account of the manufacturing industry in Kenya. Neither is it a conventional book in the sense that all chapters are sequenced and structured in order to give the reader a ‘complete’ picture of some aspect of these industries during the early 1990s. Instead, it is more of a personal academic record of my early years at the department of economics at Göteborg University, featuring five empirical papers on Kenyan manufacturing appearing in the order in which they were written. The subsequent papers were not planned as the first ones were in process. Some minor changes of methodological views do occur therefore, which are an unavoidable part of such a thinking process.

All contributions are based on the Kenyan part of the Regional Program for Enterprise Development (RPED) comprising of surveys of enterprises conducted in a number of countries south of the Sahara. The project was launched by the World Bank in the early 1990s to find explanations for the sluggish supply response in African manufacturing to several years of structural adjustment. The research agenda was ambitious covering a wide range of topics, including firm dynamics, institutions, labour markets, policy, regulations and support services. The institutional environment was a principal area of interest.

My objectives are, for natural reasons, less ambitious and focus on technical efficiency, factor substitution relationships, and differences between formal and informal small firms. Specifically, the papers analyse: the association between technical efficiency and firm size and age; the elasticities of substitution between capital, skilled and unskilled labour; the determinants for productivity, and formal-informal differences of small firms with respect to production, growth and human capital. The main thrust is empirical, contributing to the relatively scarce body of in-depth evidence on African manufacturing, but the papers may also be of some independent methodological interest.

In all papers, firm size is central. This is motivated by the skew size distributions of enterprises prevailing in Sub-Saharan Africa where an extremely large number of small establishments coexist with a few large ones, leaving a gap in between. This gap is referred to as the 'missing middle' in the literature and the discussion on its underlying causes has a long history. Interest is further stimulated by the fact that the smallest segments appear to be growing in the developing countries, often employing about two times as many people as the public sector (Liedholm and Mead 1999). Whether this is to be seen as an indicator, or even a cause, of underdevelopment or not is a debated issue. Although small and medium-scale enterprises are believed to play important roles in the economy, their number and proportion would shrink substantively, particularly in manufacturing, if they were to follow the path set by the industrialised world. Nevertheless, the literature suggests that small firms might contribute to economic growth in a number of ways.

First, small firms may provide employment for large numbers of unskilled workers, which could be desirable from an allocative efficiency point of view and for poverty eradication reasons. However, the argument presumes that small firms utilise resources *technically* efficient, which is not self-evident as stressed by Little (1987) and a topic to which we return to later. A second argument for small-scale production is that it provides training opportunities for young workers. The point is valid if the skills learnt are not obsolete.

Thirdly, a large population of small firms may constitute a 'seedbed' from where the most viable enterprises are singled out by market pressure and grow. Such processes may be limited in developing countries, however, as already noted by Hoselitz: '…too many small firms fail and too few prosper. It is not the fact of vulnerability as such which is characteristic of dwarf and small enterprises in underdeveloped countries, but the high incidence of failure, as compared with European countries or Japan.' (1959:616). The observation appears sadly relevant for manufacturing in most Sub-Saharan countries even today, four decades later. A final argument is that innovation rates are sometimes claimed to be higher. Empirically there is little support for this proposition in industrialised economies. Although a 'little bit of bigness' is good for innovation and invention, there is no clear relationship between firm size and the rate of innovation (Brock and Evans 1989). In developing countries there exists some evidence that small firms are able to establish market niches and successfully compete with larger firms by being more innovative and flexible.

All these arguments for small-scale production are related to the vaguely defined sub-discipline 'development economics' to which this dissertation belongs. In section 1 I briefly review the role and reasons for existence for small firms advanced by different branches of this literature. Following this broad overview I attempt to gradually narrow down the perspective. Major growth constraints for small firms in Sub-Saharan Africa are discussed in section 2. A description of the manufacturing sector in Kenya is given in section 3 followed by details of the surveys and data handling procedures in section 4. Since these topics have been widely covered by previous publications[1], and because I have nothing novel to add in these two latter sections, they are kept very short. A summary of the main findings, potential errors and ideas for future work in the area concludes this overview.

1. Small firms in development economics

The early development economics literature advanced a rather pessimistic view of small- and medium-sized enterprises. These represented, it was argued, an 'archaic' mode of production inherited from colonialism and was regarded as a disequilibrium phenomenon destined to become extinct as the economy grew (Fafchamps 1994). In essence, this perception was not altered when the 'missing middle' was discovered in the mid-1960s. Developing countries, whose firm size distributions resembled those of western Europe in the late 1800s, were expected to follow the same grow path led by large-scale industry

[1] See Department of Economics, Göteborg University, and Department of Economics, University of Nairobi, (1993, 1994 and 1995). Also see Bigsten and Kimuyu (1998) and various issues of Ekonomiska Studies utgivna av Göteborgs Universitet.

as in most industrialised countries (Anderson 1982). Little attention was given to the role of small firms in the development process, with the exception of Hoselitz' (1959) who put forward a number of reflections on 'small industry in underdeveloped countries' preceding much of today's thinking on the subject. He observed that size distributions differed substantively between countries such as India, Japan and Western Europe and proposed that the nature of competition, degree of vertical integration and entrepreneurial networks were critical factors behind these differences.

The pessimistic view on small-scale production in the early literature was challenged in the 1970s with the introduction of the 'informal sector' which initiated a flood of empirical studies. Definitional and measurement problems have made the concept less popular in the 1990s, but the positive view on small-scale production is preserved in 'new' directions of the literature on flexible specialisation, enterprise clusters and collective efficiency. Besides these perspectives more oriented towards development economics and development studies, firm size also plays a prominent role in the more traditional economic analysis. This mainstream literature is presented in the subsection below, followed by reviews of the literatures on the informal sector and the 'new' directions. The reader will understand that these reviews are kept to minimum length.

Mainstream economics

There is no general theory of the determinants of firm size in economics. Partly this probably reflects the neglect of the subject in economics. In his survey on 'small firms in economic theory', You (1995) proposes a fourfold division of the literature in which firm size plays a role. The first is the technological, or microeconomic, approach where firm size is set by the minimisation of average costs, which is in turn determined by the technology. If the cost curve is flat, optimal firm size is indeterminate; if downward sloping, it is infinitely large; and if the curve slopes upwards, infinitesimal. But, an upward sloping cost curve is contradictory because nothing prevents the duplication of production plans at lower scales within the same firm. Thus, optimal scale is either indeterminate or infinitely large, which is not very comforting for a theory of firm size. There are two solutions to the anomaly: one is the existence of a fixed and non-duplicable firm-specific input such as ability, and the other that a firm exhibits decreasing returns to organisation. In both cases, the firm's *combined* costs curve would be U-shaped thereby defining a unique economic size.

The second approach is the transaction costs theory. Without such costs, there is no reason for a firm to exist at all because bargaining, monitoring and contracting would be perfectly costless. Such costs exist both outside and inside the firm. Efficient size is therefore determined where the marginal transaction costs within the firm equal the market transaction costs. If market transaction costs fall, firm size may also fall. Fafchamps (1994) argues that transactions costs for small firms in developing countries might be lower compared to those of larger companies. For example, monitoring costs for labour are lower because of smaller organisations and the use of family manpower. Being located closer to the consumer reduces the costs for acquiring market information, and so on.

The third class of explanations for firm size is based on the industrial organisation literature. In contrast to the technological and transactions costs approaches, where efficiency reasons are central, the industrial organisation literature emphasises imperfect competition as the principal determinant of size. These include transportation costs, creation of market niches, and monopoly power.

A fourth line of thought is drawn from the firm growth literature. Early contributions modelled this process as an outcome of purely stochastic events, whereas later developments incorporated efficiency and managerial ability into the analysis. An important contribution is a model proposed by Jovanovic (1982) in which efficient firms grow over time and inefficient ones remain small or exit. Evidence from the US indicates that the growth and hazard rates of firms decrease with their age and size, which is consistent with this model (for a survey see Sutton 1997). MacPherson (1996) presents similar findings for micro and small firms in five countries in Southern Africa. The theory also predicts that technical efficiency is increasing in firm size and age. This hypothesis is tested on the Kenyan data in papers 1 and 2. Still, this literature may be of limited usefulness in many LDCs since it cannot explain why the *number* of small firms increases rather than their size.

On a more general level, it has been questioned whether theoretical work based on equilibrium conditions can take us very far in the understanding of why small firms grow in number rather than in size in developing countries (Liedholm and Mead 1999). Markets in such countries are often subject to various types of distortions, including repressive actions by the authorities. Of the views presented above, the most relevant for our purposes are probably the theories based on transaction costs and industrial organisation. As will be evident below, these approaches share some of the ideas advanced in the literature on the informal sector and the new institutional economics.

The informal sector

As noted above, the introduction of the informal sector in the development literature represented a shift to a more positive attitude towards small-scale production. The informal sector provided, it was argued, shelter and income opportunities for the urban poor and was, as such, of prime interest for policy makers and donors with poverty eradication on the agenda. The concept was adopted by several disciplines, most of them outside mainstream economics, and numerous empirical studies were conducted especially during the 1970s. Making it operational in the field often proved complicated however and a range of different definitions was used, leading to confusion and serious critique of the concept in the 1980s. The key definitional variable of an informal enterprise in most of these studies was the relationship vis-à-vis the state. An informal firm did not comply with the legal requirements including licensing, minimum wages and tax payments. Direct criminal activities were excluded in most definitions: the illegality of informal production stemmed from its unregistered mode of operation and not from the nature of the economic activity *per se*.

Whether the informal organisation of production possessed some economic potential or merely was a euphemism of poverty was intensively debated during the 1970s and 1980s. Harriss (1990) identified four main strands of this debate according to the authors' views on formal-informal linkages and informal growth prospects. For those with a pessimistic view, the sector was either *exploited* or *marginalised* by the formal sector. The more optimistic saw an economic potential in the informal sector, which either was *dual* or *complementary* to the rest of the economy.

A problem with all these interpretations is the observed heterogeneity of the subject: it is not hard to find evidence for each of these four views. Indicative of this is the fact that some divide the informal sector into dynamic and stagnant segments. This puts the usefulness of the whole concept into question, as does the fact that informal enterprises dominate the smallest size strata. To this end we may ask: Do formal small firms really exist? And if they do, are they different from informal ones? If the answer is negative to one of these questions, the concept becomes synonymous with small firms, which is the preferred term in a number of more recent contributions (see Little 1987, and the references in the next subsection). Nevertheless, the last paper of this dissertation suggests that formal and informal small firms in Kenyan manufacturing *are* distinct in a number ways.

The cardinal contribution of the informal sector literature is its focus on the role of the state in shaping the business environment for small and large activities. Industrial policy in many LDCs has traditionally been designed with large-scale establishments in mind, partly inspired by the early development literature. Taxes, regulations and bureaucratic requirements would therefore constitute a relatively higher cost on medium and small firms. Operating informally without some or all of these legal requirements reduces such costs, but may at the same time constitute a barrier for growth for small firms. The behaviour of the state can thus be a factor behind the missing middle in Sub-

Saharan Africa: cost-effective scales of production is either relatively large or very small (Fafchamps 1994).

Besides cost-advantages, small-scale establishments can also benefit from adopting flexible technologies and organising in clusters, as proposed by the 'new' directions in the new institutional economics tradition, which appear to have replaced parts of the literature on the informal sector.

'New' directions

The 'newness' of the more recent work on small firms within the institutional economics approach is its focus on the interactions between them. Such interactions are not absent in the analyses by mainstream economics or the informal sector literature, but the novelty here lies with how inter-firm cooperation can directly enhance the performance of an individual unit. The view was partly inspired by the successful conglomerates of small firms in the Emilia-Romagna region in northern Italy and in Japan. These cases draw the attention of a number of scholars. Piore and Sabel (1984) explained the success by 'flexible specialisation', referring to the observed ability of these enterprises to quickly adjust and specialise by vertical integration. The process requires close collaboration among firms and thus, in the words of Piore and Sabel (1984:275), 'works by violating one of the assumptions of classical political economy: that the economy is separate from society.' They also saw flexible specialisation as an appropriate industrialisation strategy for the third world to be preferred to copying the mass-production model of the advanced nations.

Pyke (1994) identified four foundations behind the achievements in Emilia-Romagna. These were: close inter-firm cooperation, especially vertically; joint engagement in collective action such as provision of specialised services and promotion of the industry; dissemination of production-related information among firms; and an interventionist policy by the local government, including supportive institutional bodies for service and research.

It is an open question whether the clusters of small firms frequently observed in developing countries can provide benefits on the same scale. Research on the subject by the institutes for development studies at the universities of Sussex and Nairobi provides mixed results (Schmitz 1995, McCormick 1998). The advantages of locating side-by-side, denoted 'collective efficiency' in this literature, are certainly greater than the loss of profits due to increased competition, but examples of clusters in developing countries that have exploited such efficiency sufficiently to break into export markets are still rare. Brilliant exceptions include Sinos Valley in Brazil, a cluster of 1800 small and medium firms which has became a major export industry of footwear, and Sialkot in Pakistan, a cluster of 300-350 enterprises with an average size of 20 workers that exports stainless steel medical instruments for markets in North America and Western Europe.

Referring back to the discussion on mainstream economics above, it appears that the main thrust of this literature is on how small firms through cooperation can reduce external transaction costs and simultaneously maintain low internal transaction costs by remaining small. Thus, the ratio of external to internal marginal transaction costs fall, inducing a subsequent decrease in efficient firm size. In any case, it enables small firms to operate relatively efficiently on a small scale.

This review has highlighted a number of potential determinants of firm size. Since small-scale enterprises are heterogeneous, so are the theories explaining their roles and functions, and it is therefore neither necessary nor desirable to try to identify one single theory. There is probably some truth in all perspectives. Technology and stochastic elements clearly have some impact, as have the industrial organisation theories on imperfect competition. Later contributions on the informal sector and on clusters of small firms have stressed the role of the state and transactions costs (Feige 1990). Depending on the combined effect of all of these factors, efficient firms may appear in many different sizes. However, none of these theories are really able to fully explain the missing middle. This motivates the study of the growth constraints small firms face, which is the purpose of the next section. The discussion is now confined to manufacturing in Sub-Saharan Africa, following my intention to gradually narrow the focus towards my sample data, although many of the points raised may also apply elsewhere.

2. Growth constraints for small firms in Sub-Saharan Africa

There is no shortage of ideas in the literature to explain why small firms stay small in the region. More scarce, perhaps, are analyses on which constraints are the most important ones and what policy can do to mitigate them. In addition to low growth rates, African manufacturing firms spend very little, if anything at all, on research and development of new products (Biggs *et al* 1996). One can presume that the factors explaining this also hinder the expansion of small firms to some extent.

These growth constraints can be classified in different ways. Below I have chosen to group them into institutions, capabilities, tastes and demand.

Institutions

In the new institutional economics tradition, institutions are sometimes defined as 'the rules of the game', or 'any constraint that human beings devise to shape human interaction' (Pedersen and McCormick 1999:111). As such the definition is fairly broad, incorporating not only government and private organisations, but all cultural and social constructions that affect human behaviour.

Pedersen and McCormick suggest that a major factor behind the failures of many structural adjustment programs in the region is that institutions generally are too fragmented. The industrial sector in a post-colonial African state is typically three-tiered, consisting of a parastatal, a formal and an informal part. The tiers arose as the state after Independence sought to balance the dominance of non-indigenous groups by forming government-owned large-scale companies led by Africans. These were usually capital-intensive, closely knit to political interests and poorly integrated with existing industries. The incapacity of these cooperations to absorb the influx of labour from the rural areas in later decades contributed to the creation of the third tier, the informal sector. An example illustrating the poor integration of the tiers is the financial market, where the non-indigenous business spheres usually have their own banks that seldom grant loans to outsiders. Similar tendencies have been recorded with respect to access to premises and markets. In the political arena, on the other hand, the picture is reversed and the non-indigenous groups are left with little influence.

The fragmentation described by Pedersen and McCormick may hinder the growth of firms in three major ways. One is the market-limiting effect of being confined to one tier; this refers likewise to final sales as to the supply of inputs. Second, savings may not find their way to the most productive investments unless they originate from within the same tier, which cannot be expected to be generally the case. Finally, the level of competition is restricted, further depressing the incentives to invest and innovate.

Fafchamps (1994) advances the power of market institutions to assist firms in enforcing contracts as a critical institutional factor that may constrain enterprise growth. If they are insufficient, which is more often the case than not, entrepreneurs restrict their engagements into contractual relationships to networks of friends, relatives and kin. Better functioning of market institutions would reduce such fragmentation and widen the markets. Appropriate policies should therefore involve bringing the judicial process closer to the small firms and setting up special courts for conflict resolution.

Capabilities

Another critical factor that may constrain the growth of small firms is shortage of technical and managerial capabilities, or simply put, skills. Hamermesh (1993) believes that the scarce factor in developing countries is skill, rather than physical capital, and that the two inputs could be complements in production. If so, a given increase in the supply of capital may have little effect on output compared to an increase in skills. To analyse such patterns, one must distinguish between unskilled and skilled labour, which I do in paper 3.

Pack (1993) argues that skill is the 'other half of the scissor' for successful structural adjustment, the other being getting prices right. Pack underlines his argument with an examination of the Asian success stories which he asserts rests on massive human capital accumulation. The lack of skill in Sub-Saharan Africa not only constrains actual operations of firms, but also limits technological diffusion among them since the labour markets are too small to allow for sufficient worker mobility. Given the weak educational infrastructure on the continent, Pack proposes that national policies should involve contracting of highly skilled expatriate experts for periods of two to five years, and sending cohorts of students abroad for master degrees. Multinational corporations might also be useful in national human capital formation, provided that workers receive training relevant to the local industry.

The skill variable in the analyses of Hamermesh and Pack mainly refers to technical capabilities which, loosely speaking, is the ability of the workforce to utilise equipment and technology efficiently in production. Another important aspect of capability is the managerial ability required to administer an efficient labour force. Some argue that such abilities, including accounting skills and a capacity to handle the formal organisation of production on a larger scale, are in short supply in African small firms (Fafchamps 1994).

Another problem with the managerial culture in Sub-Saharan African is their steep hierarchies and little delegation which reduces the incentives for skill formation and innovation, and also limits the training space for would-be entrepreneurs (Pedersen and McCormick 1999). This deficiency, inherited from pre-colonial and colonial times, limits the performance of large organisations including large firms. It is doubtful whether it can be changed by education alone.

Tastes

Besides institutional and capability constraints, firm growth may be hindered by the simple fact that its owner does not want do grow. A natural example is when growth in itself is associated with a substantial degree of risk, including bulldozing of the entire plot, which is a real-world threat in Kenya today (King 1996). Given the social and economic consequences of default in a harsh developing economy, such risk-aversion is understandable. McCormick (1992) identified four risk-managing strategies in Nairobi's small-scale manufacturing, including flexibility, only producing standard products, diversifying rather than expanding a single business if possible, and not using fixed assets as collateral for loans.

Another reason for not being willing to grow is that success is not regarded as a private affair but rather as a public good to be shared with friends and relatives. This makes the returns to success decrease beyond a certain threshold. An entrepreneur may then prefer to give away valuable business information to others rather than using it himself, resting in reassurance that the favour will be returned one day if needed.

Demand

A final growth constraint is the level and quality of demand for the output by small firms. In a recent study of Nairobi's garments producers, weak demand was found to be a principal factor behind slow growth rates (McCormick, Kinyanjui and Ongile 1997). Most donor activities aimed at supporting small firms, however, are typically supply-oriented, often including training schemes and credit. Demand is seldom addressed, which is understandable as it is harder to tackle in a single project. But the demand issue could certainly be mainstreamed in other development projects by putting an increased share of purchase orders with local producers.

An example is the Accountant General's department in Dar Ss Salaam, my present workplace, which has been furnished by IKEA as part of Swedish development aid. In my apartment, paid with the same money, the IKEA fibreboard pedestals and tabletops are slowly falling apart because they were not designed for the humid climate. Had the furniture been purchased from local carpenters they would not only have been cheaper and more durable, but also provided a stimulus for the small-scale wood sector in Tanzania, well in line with the stated objectives of Swedish overseas aid. The anecdote may appear trivial, but the scope for increased government and donor purchases from small-scale enterprises has been emphasised before (Hoselitz, 1959; Liedholm and Mead, 1987; Little, 1987).

3. Manufacturing production in Kenya

Although the manufacturing industry in Kenya is relatively well developed by east African standards, it nevertheless exhibits most of the characteristics described in the previous section. Like many countries in the region, it pursued import substitution policies in the 1960s and 1970s. This involved licensing of foreign multinationals, such as Bata, while other activities consisted mainly of simple assembly and compounding of imported materials. Overall, the strategy never managed to spur domestic supply of the whole chain of intermediate inputs, nor did it succeed in fostering research and development. An overvalued exchange rate led to excess investments in some sectors, and low capacity utilisation as a result (Sharpley and Lewis 1990). The second-hand market for physical capital is very weak. Resource and labour-intensive production is still dominant in Kenyan manufacturing industries, and there exist large 'holes' in the industrial base: there is little chemical industry and almost no high precision metal production (Biggs *et al* 1996). The food sector is the most advanced and produces the largest output within manufacturing. In paper 4 it is shown that this sector is also the most productive.

The three-tiered structure discussed above is particularly accentuated in Kenya. The government expanded rapidly after Independence and is dominated by Kenyans of African origin, while the formal industrial sector is composed largely of Kenyans of Indian or Pakistani origin. Several initiatives have been taken by the authorities to encourage the formation of an African industrial class, but these have so far been rather unsuccessful. Part of the reason for failure probably lies with the half-hearted and inefficient implementation of these initiatives. Coughlin and Ikiara (1988) note that Kenya has an impressive number of agencies and institutions with the right stated objectives but with poor records of implementation.

During the 1970s import substitution policies were strengthened, but later crumbled as the country was struck by external shocks such as the oil crises that led to severe balance of payments problems. The structural adjustment programs that followed, together with the liberalisation of foreign trade and financial markets, have provoked social unrest and policy reversals during the 1980s and 1990s. The business environment was particularly unstable during the early 1990s, involving frequent changes in industrial and trade policies. Lack of transparency fuelled corrupt practices, and outright violence erupted during the 1992 elections. Hence, the RPED surveys were conducted in a habitat infested by substantial risk (Bigsten and Kimuyu 1998). Weak domestic demand and increased competition from imports were also troubling manufacturing entrepreneurs during the survey years.

4. Survey and data handling

The Kenya mission of the RPED initiative involved three survey waves, undertaken in February-March 1993, May-June 1994 and August-September 1995. The interview teams consisted of staff from the Departments of Economics at the Universities of Nairobi and Göteborg. Unfortunately, I did not participate. The data generally refers to the latest year of operation, which means that the data mainly covers the period 1992-94. A total of 658 observations on 275 firms in the food, wood, textiles and metal subsectors, located in Nairobi, Eldoret, Nakuru and Mombasa were made. Out of these, 169 appeared in all three waves, whereas the remaining firms were observed only one or two times due to various known and unknown reasons, including default, disappearance and refusal to be interviewed again. The sectors covered comprise about 73% of manufacturing employment in Kenya, hence providing a relatively comprehensive picture of the country's manufacturing sector. Further details of the sampling procedures, stratification and statistical sources are given in Bigsten and Kimuyu (1998).

Since the main analytical tool in this dissertation is the microeconomic theory of production, principal variables of interest are output and inputs. The output variable is defined as the value of all output produced by the firm the previous year. A problem associated with this variable is that a few firms engage in side-activities such as servicing and trading which may utilise inputs to some extent. Due to the erratic reporting on these variables they are not included in the definition of the output variable. Capital is defined as the replacement cost of capital of the existing machinery and other equipment employed in production. Missing or implausible values were imputed using past or future values and accumulated investments when possible. Buildings and land are not included because of a large number of missing values.

Labour was either measured as total wages including allowances or as the number of workers. A small number of missing values of wages were imputed using past or future mean wages multiplied by the number of workers. The division of labour into skilled and unskilled is described in paper 3. Intermediate inputs comprise costs for raw materials, solid and liquid fuel, electricity and water. Other costs were not included since they were not consistently recorded in all surveys. All monetary variables are measured in 1992 Kenyan Shilling using appropriate deflators derived from various publications from the Central Bureau of Statistics for which details are given in paper 1.

5. Findings, potential errors, and ideas

The hypotheses addressed in the five empirical papers of this dissertation are inspired by the discussion above. They are all independent applications in microeconomic production theory and the results are interpreted in light of the literature on the prospects and hardship for manufacturing enterprises in developing countries.

The first two papers investigate whether technical efficiency is increasing in firm size and age as proposed by the Jovanovic model. The evidence supports this claim with respect to firm size, but not age, which is consistent with previous evidence reviewed. These results, obtained using a stochastic frontier production function model, are confirmed in paper 2 which addresses the same hypothesis using data envelopment analysis. Besides the Jovanovic-type of selection mechanism in which the fittest grow larger, this result can also be interpreted as evidence that the disadvantages of operating small, including financial constraints and little government support, outweighs the potential advantages, such as collective efficiency and flexibility.

Paper 3 addresses the skill factor as an input in production. The results indicate that skilled and unskilled workers can be more readily substituted between each other than with capital, which contests the claim that skill is a complement to capital. However, these results are shaky given the difficulties associated with capturing skill. There also exists a positive relationship between firm size and capital intensity. Estimated translog production functions suggest this is due to non-homothetic technologies and to different input prices for small and large firms. The rejection of homotheticity may have implications for economic models if these rely on the assumption of linear expansion paths such as in the Cobb-Douglas specification of technology.

Paper 4 is a broad analysis of the performance of the subsectors in terms of technical efficiency and productivity. An interesting result, subject to some ambiguity, is that growing firms are more productive than contracting ones, which suggests that turbulence may stimulate overall productivity. Several variables do not explain the variation in productivity in the analysis, including exporting, skill, access to an overdraft facility and foreign ownership.

The last paper addresses the debate on the usefulness of the informal sector concept. To settle the issue with respect to Kenyan manufacturing, a subsample of small firms with twelve workers or fewer was analysed in order to investigate whether formal and informal small establishments really are different. The evidence suggests that they indeed are different, which indicates that the concept may be of analytical value. There are some signs of informal economic potential. Also, technical efficiency varies much more with the ethnicity of the owner than with formality status, which in part could be explained by the distinct supporting networks that the two groups operate in.

The five papers comprise a somewhat diverse body of evidence on recent developments in Kenyan manufacturing that will contribute to the empirical literature on small firms in developing economies. Besides the empirical findings, the papers may also be of some independent methodological interest. Comparisons of stochastic frontier production function estimates and data envelopment analysis with respect to the measurement of technical efficiency and the analysis of its determinants is conducted in paper 2. Paper 3 not only tests the hypothesis of homothetic technology, but also quantifies it in terms of how factor bundles change with relative prices. Some suggestions on how to conduct econometric analysis of small informal firms in included in paper 5.

Lastly, I will make only a few suggestions for future work based on ideas that have struck me during the near three years I have worked on this dissertation. With respect to the RPED initiative, I believe that the very same reasons that motivated its initiation in the early 1990s also motivate its continuation in some form. As described above and elsewhere, the survey years were plagued by economic and political turbulence, and it is warranted to investigate whether the estimated relationships also holds over longer periods of time and under more stable market conditions. There is also a need for comparative studies using similar data from countries in the region and elsewhere.

More effort is also needed to quantify and identify the sources of measurement error. For instance, it can be expected that flows are gauged less accurately than stocks, and also that firms with proper accounting provide more precise information than those that do not, and so on. Assessments of the magnitude of such sample noise can be explicitly incorporated into the empirical analysis, making it more robust and possibly more accurate. Future surveys need to improve the coverage on firm history in order to facilitate the mapping of the graduation process of firms which is vital in the analysis of firm growth. The ethnic factor and the influence of networks also need more detailed analysis given their profound impact on the performance on small firms

On the methodological side, there is certainly room for investigating the same hypotheses with alternative approaches. Suggesting such alternatives here is, however, beyond my present ambitions.

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Dar Es Salaam
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FIRM SIZE, AGE AND EFFICIENCY:

Evidence from Kenyan manufacturing firms[#]

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Abstract: Translog stochastic frontier production functions are estimated using an unbalanced panel of 235 Kenyan manufacturing firms in the food, wood, textile and metal sectors. The sectors are estimated individually and pooled together in order to investigate whether technical efficiency is systematically related to firm size and age. The evidence suggests that firm size has a positive and significant effect in the wood and textile sectors, and also in the pooled model in which this effect becomes stronger as firms grow older. The age effect is less systematic and insignificant in the pooled model and in all sectors except textiles.

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1. Introduction

A distinctive feature of the unsatisfactory economic performance of the countries in Sub-Saharan Africa is the slow rate of technological progress in the manufacturing sectors. The output of these sectors is constrained by several factors, of which two stand out; namely low levels of investment, and low total factor productivity. It is an established fact that the rate of resource accumulation in this area is lagging behind that of other regions in the world. Also, the average rate of technical efficiency change has been very low for more than a decade, and even negative in recent years (Bigsten, 1996). In this paper, we are concerned with the latter of these two issues.

At the firm level, the study of the determinants for technical efficiency is related to the literature on the size and the size distribution of firms in developing economies. Some researchers advocate promotion and support of small firms on the basis of both economic and welfare arguments (You, 1995). It is argued, for instance, that an expansion of the small firm segment leads to more efficient resource allocation, less unequal income distribution and less underemployment because small firms tend to use more labour-intensive technologies. Furthermore, a large number of small firms may constitute a seedbed for young entrepreneurs. In addition to these arguments, technical efficiency of small firms may be higher as a result of their being exposed to more competition than larger firms.

On the contrary, a theory by Jovanovic (1982), developed as a model of firm growth, leads to the conclusion that larger firms are more efficient than smaller ones. This result is an outcome of a selection process, in which efficient firms grow and survive, while inefficient firms stagnate or exit the industry. Although the Jovanovic model has been developed in various directions recently, for instance by Hopenhayn (1992) and Ericson and Pakes (1994), the basic prediction of a positive size-efficiency relationship remains. Another implication of the selection process in these models is that technical efficiency is positively related to firm age. New firms are unaware of their abilities, and need time to decide on their optimal size. Over time, the least-efficient firms exit, leaving a technically more-efficient population of firms for every given age category.

In these models, age has no effect on the efficiency parameter itself which either is fixed, as in the Jovanovic model, or determined by the uncertain outcome of an investment schedule, as in the Ericson and Pakes model. A natural extension of the models of firm growth is therefore to incorporate learning effects, so that firms become more efficient as a result of its growing stock of experience in the particular industry. Indeed, the literature on learning by doing dates back longer than that of selection, and is, in turn, related to the literature on endogenous growth theory, industrial organisation and trade theory.

From a policy perspective, empirical evidence on the size-efficiency and the age-efficiency relationships may prove useful in order to direct resources to firms which employ them more efficiently. Should industrial policy be neutral with respect to size, or favour a certain size category of firms? Should it encourage a high turnover of firms in industries, so that the mean age of firms decreases, or the opposite? Should policies be general in their design, or differ among specific sectors?

The purpose of this paper is to address these issues by evaluating the impact of firm age and size on technical efficiency for manufacturing firms in Kenya. A stochastic frontier production function, of the type proposed by Battese and Coelli (1995), is estimated simultaneously with the parameters of a model for the technical inefficiency effects.

The data for our empirical analysis consist of an unbalanced panel of Kenyan manufacturing firms in the food, wood, textile and metal sectors, observed during the years 1992-1994. The sample covers a wide range of firms with regard to size, age and other characteristics. The paper proceeds with a review of the Jovanovic model and some other models in Section 2. Special attention is given to the relationships between firm age, size and efficiency. In Section 3, the manufacturing sector of Kenya is discussed, together with the sample data involved. The stochastic frontier production function is presented in Section 4, followed by the empirical results in Section 5. Section 6 summarises and concludes the paper.

2. Firm size, age and efficiency

In traditional neo-classical economics, there is no reason to expect that firms of different sizes and ages would operate at different levels of technical efficiency. Although the size of a competitive firm may be determined as the minimisation of the average cost of production for the best-practise frontier, deviations from it are basically left unexplained. Nor are age and experience considered as factors influencing technical efficiency.

In the literature on firm growth, however, efficiency plays a significant role in the growth and dissolution of firms. A common reference in this area is the Jovanovic (1982) model, which incorporates elements from the stochastic and the entrepreneurial theories of firm growth. Although the Jovanovic model originally was developed as a theory of firm growth, from which hypotheses regarding the life-cycle of firms can be derived, it can also be used to estimate relationships between firm size and efficiency, and age and efficiency.

Jovanovic assumes a competitive industry, with a known time-path of future output prices, where firms differ in efficiency. Total costs are $\theta c(y)$, where $c(y)$ is a cost function common to all firms and $\theta>0$ is a firm-specific fixed inefficiency parameter. The static profit-maximisation problem facing firms is

$$\max_{y} \quad \pi = py - \theta^{*} c(y) \tag{1}$$

where θ^{*} is the firm's expectation of θ conditional on the information available to the firm. The change in profit-maximising output, given a change in θ^{*}, is[1]

[1] Obtained by differentiating the first-order condition, $c'(y)=p/\theta^{*}$, with respect to θ^{*} and solving for $\partial y/\partial\theta^{*}$.

$$\frac{\partial y}{\partial \theta^*} = -\frac{c'(y)}{\theta^* c''(y)} \quad , \tag{2}$$

which is negative because costs are assumed to be convex, i. e. $c''(y)>0$. Firm size, in terms of output, is consequently positively related to efficiency. A firm considers its efficiency level as given, and adjusts its scale of operation accordingly. The expressions in (1) and (2) clearly state the direction of the causality inherent in this model: it is efficiency that determines firm size, and not the other way around.

As firms enter the market, however, they are unaware of their individual efficiency and consider them as random draws from a known population of efficiency levels. Consequently, all firms have the same θ^* and choose the same size in the first period. Once entered, firms update their θ^* after every period, based on the difference between expected and realised profits. Firms whose realised profits exceed expected profits adjust their θ^* downwards, i.e. they expect themselves to be more efficient in the next period. Likewise, firms whose actual profits were lower than expected adjust their θ^* upwards. To infer the correct value of θ, a firm needs several periods of observations because realised profits are affected by unpredictable and firm-specific shocks.

Over time, the θ^*s of firms approach the actual values of their inefficiencies. As a result, efficient firms grow and inefficient firms decline. Jovanovic assumes that firms below some threshold level of efficiency exit the industry. As these gradually leave the market over time, mean efficiency levels increase for groups of firms of the same age. Firm age is consequently positively related to efficiency.

The Jovanovic model has been considered as an important step towards a more realistic theory of firm growth. Nevertheless, at least two major points of criticism can be raised against it.

The first is the assumption of a convex cost function. By the principle of duality, this restricts the technology to decreasing returns to scale. A relevant question is then how to proceed if this condition is not met. In fact, few applications in the production literature have presented evidence of decreasing returns. The convexity assumption is given little attention in the literature. However, in a mathematically sophisticated elaboration of the Jovanovic model, Hopenhayn (1992) succeeds in duplicating most the above results under constant returns to scale.

The second point of critique concerns the assumption of a fixed inefficiency parameter. Once firms start their operations, their efficiencies cannot be altered by, for instance, investing in training, getting more experience or entering export markets. This assumption leaves little room for policy guidance, since support programmes directed at enhancing efficiency of particular firms would have no effect.

In essence, this restriction assumes away one of the most dynamic processes taking place within industries, namely learning by doing. The study of this subject dates back to the 1930s for the developed economies. Since then, models have been developed to describe learning curves and their contribution to productivity growth at both sector and macro levels (Malerba, 1992). In development economics, the concept has played, and continues to play, a significant role. Several countries in East Asia, in particular Japan and The Gang of Four, invested heavily in foreign technology during the early phases of their industrialisation. Over the years, the handling and practical experience with their equipment generated considerable learning effects, which often are claimed to have been important factors behind their economic success (Pack, 1992).

An important empirical regularity, suggested by various industry-level studies, is the existence of strong diminishing returns in the 'learning-by-doing process' (Young, 1991). Although there is an ongoing discussion on whether the gains in technical efficiency from experience are eventually entirely exhausted, most researchers seem to agree that these gains become smaller over time. In this literature, most analyses are focused on industry-level learning processes, and it is an open question whether diminishing returns also prevail at the firm level.

The literature on learning by doing thus provides a number of arguments for positive effects of experience on the efficiency parameter. A model by Ericson and Pakes (1995) proposes yet another channel through which this parameter may be altered, namely through direct efficiency-enhancing investments by the firm. The outcomes of such investments are, however, uncertain and depends on a number of factors, including the behaviour of rival firms. In the beginning of each period, the firms must decide whether to exit, to continue at current efficiency levels, or to invest. Entrants begin with relatively low levels of investment. Over time, firms whose investments are successful grow and invest even more, while less-fortunate firms maintain their current sizes or leave the industry. As a result, efficient firms are generally larger and older than entrants, but since the payoff from the investment may change in any given period, young firms can overtake older ones in terms of efficiency.

Empirical evidence

The Jovanovic model has been put to empirical test in studies of firm growth by Evans (1987), Hall (1987), and Dunne, Roberts and Samuelson (1989) on US data, and by MacPherson (1996) on Sub-Saharan data. The findings suggest that firm growth decreases with age and size which is consistent with the Jovanovic model. The issue of whether the convexity assumption is plausible is not addressed in any of these studies.

Empirical studies of the sources of technical efficiency have considered the effects of age and size of firms, and other variables. Table 1 presents a list of relevant studies on manufacturing sectors in developing countries. Broadly speaking, the findings are consistent with the hypothesised size-efficiency relationship, but not with the age-efficiency relationship, in the selection models above.

Firm size appears to have either a positive or a zero correlation with technical efficiency. The only exception to this pattern is presented in the Biggs, Shah and Srivastava (1996) study, where an inverted U-shaped association between firm size and efficiency is estimated. Hence, the size-efficiency relationship is negative for large firms and positive for small firms. The pattern is detected in three of the four sectors, where medium-sized firms (50-199 workers) are the most efficient.

The age-efficiency relationship, on the other hand, is both negative and positive. For example, in the Little, Mazumdar and Page (1987) study, technical efficiency decreases with firm age in three of the five analysed sectors. This result is explained as reflecting the fact that older firms tend to employ capital of an older vintage, which is less productive than the industry average. The same study also notes that efficiency levels increase with firm size, but when taking into account the effects of capacity utilisation, and working experience of the manager and the labour force, the size effect is insignificant.

An interesting association between age and technical efficiency is discovered in a recent study by Mengistae (1996). Stochastic production functions are estimated and efficiency scores regressed (using OLS) on explanatory variables, including size and age. The parameter estimates for the size and age variables are positive, but the estimate for age squared is negative. This finding is consistent with the argument that learning exhibits diminishing returns. Given the parameter estimates reported by Mengistae, it is remarkable that the coefficient for the square of age is sufficiently large to make the age-efficiency relationship negative for firms older than five to eight years, depending on the specification.

Table 1. Studies of technical efficiency in manufacturing sectors in developing countries.

Study	*Country, period, industry, number of firms (N) and periods observed (T)*	*Estimation methodology*	*Correlation with technical efficiency* (+, -, 0, *or* n.a.)		*Firm size proxy*
			Firm Size	Firm Age	
Pitt and Lee (1981)	Indonesia, 1972-3 and 1975, weaving, N=50, T=3	Stochastic frontier production function	(+)	(-)	Workers
Page (1984)	India, 1980, soap, printing, foot-wear, machine tools, N=300, T=1	Parametric deterministic frontiers	(+) in machine tools, (0) in the other sectors.	(0)	Workers
Chen and Tang (1987)	Taiwan, 1980, electronics N=182, T=1	Stochastic frontier production function	(0)	(+)	Workers
Little, Mazumdar and Page (1987)	India, 1978-80, soap, shoes, printing, machine tools, metal casting, N=345, T=1	Parametric deterministic frontiers	(+) in machine tools, (0) in the other sectors.	(-) in 3 and (0) in 2 subsectors	Workers
Haddad (1993)	Morocco, 1985-89, all two-digit manufacturing industries	Fixed effects parametric approach	(n.a.)	(+)	(n.a.)
Haddad and Harrison (1993)	Morocco, 1985-89, all manufacturing sectors, N=100000, T=5	Fixed effects parametric approach	(+)	(n.a.)	Total sales
Hill and Kalirajan (1993)	Indonesia, 1986, garment, N=2250, T=1	Stochastic frontier production function	(n.a.)	(-)	(n.a.)
Biggs, Shah, and Srivastava (1996)	Ghana, Kenya, and Zimbabwe, 1992-93, food, wood, textile, and metal sectors, N=appr. 800, T=2	Mean response production function	(+) for small, (-) for large firms (see text).	(+)	Workers
Mengistae (1996)	Ethiopia, 1993, manufacturing industries, N=220, T=1	Stochastic frontier production function	(+)	(+) up to 5-8 years of age, then (-)	Workers
Brada, King, and Ying Ma (1997)	Czechoslovakia and Hungary, 1990/91, 12 manufacturing sectors, N=1000, T=1	Stochastic frontier production function	(+) in 9, and (0) in 3 subsectors.	(n.a.)	Value added

3. The Kenyan manufacturing sector & data

Since the mid-1970s, development in the Kenyan manufacturing sector has been hampered by low levels of investment, technical inefficiency of production and limited technological progress. In part, this can be explained by an unsuccessful import-substitution strategy, pursued since Independence in 1964, in which the government provided both direct support and tariff protection of the industry. At present, Kenya is abandoning this strategy in favour of a more liberal and market-orientated industrial policy. In the Sub-Saharan region, this experience is shared by many countries.

Several factors contributing to the rather unsatisfactory performance of the Kenyan manufacturing sector, in addition to the import-substitution policy, have been proposed, involving both international and national factors. On the international level, the oil crises in the 1970s, the droughts in the 1980s, and the recent withdrawal of donor support in the early 1990s, have negatively affected the business environment.

On the national level, the sector has been constrained by a number of factors, such as: shortage of technically trained personnel; insufficient infra-structure; low level of demand; credit rationing; and corruption. The widespread uncertainty among entrepreneurs and workers about the political situation and the direction of the industrial policy in general has also been an important factor. The distinctive ethnic pattern in the ownership structure, in which Kenyans of Indian and Pakistani ancestry dominate the segment of medium-sized firms, is a potential cause for social unrest.

Also the unstable macro-economic environment has posed problems for the manufacturing sector. During the early 1990s, including the years when the sample data were collected, Kenya experienced a serious recession. As shown in Table 2, the growth of GDP per capita was negative in both 1992 and 1993. Inflation peaked in 1993 at about 46%. During this period, the country experienced shortages of foreign exchange, fluctuating interest rates and fiscal deficits. In contrast, overall output growth in the manufacturing sector appears to have remained fairly unaffected by the economic turbulence.

Within the manufacturing sector, however, output levels were less stable during these years. Output indices for the four sub-sectors analysed in this study are presented in Table 2. In the bakery sub-sector, a part of the food-processing industry, output increased by over 50% in 1994 as a response to increased supplies of grain and flour products. Recent reductions in tariffs have led to increased competition from imports for local producers. The textile sector has been particularly affected by these measures, and output was almost cut in half from 1992 to 1994. The output of other sectors was comparably stable in this period.

Table 2. Selected economic indicators of Kenya.

Macro-indicators	1992	1993	1994
GDP growth	0.5%	0.2%	3.0%
GDP growth per capita	-2.3%	-2.9%	0.7%
Manufacturing sector output growth	1.3%	1.8%	1.9%
Inflation rate (CPI)	27.5%	45.8%	28.8%
Output indices of manufacturing sectors (1992=100)			
Food, total	100	100	100
Bakery products, (part of Food)	100	103	159
Wood, furniture and fixture	100	106	108
Textiles, clothing	100	91	57
Metal products	100	100	112

Source: Central Bureau of Statistics (1995)

The four sectors covered in this study represents approximately 72% of total manufacturing in Kenya (Departments of Economics, 1995). The food sector is the dominant sector in terms of output and employment, followed by the textile sector. During the years of import substitution, most resources were invested in the textile sector, and later, during the 1980s, in the food sector. Some of the investments in food production were foreign, which has been suggested as an explanation for why this sector is considered as the most productive and technologically advanced. Its output comprises a wide range of commodities, including milled grains, dairy products, canned foods, bakery and confectionery products, salt, beverages, animal feeds, and so on.

The outputs of the other three sectors covered in this study span equally wide ranges. Production in the textile sector consists of the manufacturing of garments, household items, such as furnishings and carpets, and industrial goods, including belting, rope and twine, sacks, etc. The wood sector makes timber products, furniture, wooden art, and storage and packaging materials. The products of the metal sector consist of both simple engineering work based on sheet metal (containers, utensils, window frames, metal furniture, etc.), and more sophisticated equipment to serve the needs of the railway system and the agricultural sector.

Besides these differences, there are several common characteristics of these sectors. Few enterprises have moved out of light and traditional industries into technologically more advanced ones. A large number of firms operate at low levels of technical efficiency. Furthermore, the majority of the establishments remain small. About two thirds of the firms employ ten workers or less, while only one fifth have more than 50 employees (Central Bureau of Statistics, 1995). In addition, there is a large number of very small informal firms, which are not covered by official records.

Variables

The data used in this study were collected in three interview rounds of urban Kenyan manufacturing firms during 1993 to 1995, as a part of the World Bank Regional Program on Enterprise Development (RPED). The programme was initiated in order to address the sluggish supply response of the manufacturing sectors in those Sub-Saharan countries which adopted comprehensive structural adjustment programmes in the 1980s. Detailed information about various aspects of the firms and the business environment was collected in seven African countries. For Kenya, the data consist of an unbalanced panel with 658 observations of 276 manufacturing enterprises in the food, wood, textile and metal sectors.[2]

[2] The data consist of 154, 177, 159, and 168 observations of 69, 68, 72, and 67 firms in the food, wood, textile and metal sectors, respectively.

The variables used in the empirical analysis in this paper are obtained from these data and are defined as follows. *Output* is the value of all output produced by the firm in a given year. *Capital* is defined as the replacement cost of existing machinery and other equipment employed in the production process[3], multiplied by the degree of capacity utilisation.[4] *Wages* is the total wage bill including all allowances for the firm in one year. *Intermediate inputs* include costs for raw materials, solid and liquid fuel, electricity and water.

For our analyses, output and inputs are expressed in 1992 Kenyan shillings. Separate deflators for output, capital and wages are constructed and reported in the Appendix. Observations with missing values of output and firm age were deleted, while missing values of inputs were imputed, leaving a sample of 563 observations of 235 firms.[5] Descriptive statistics of this sample are presented in Table 3.

Table 3. Summary statistics for 563 observations on 235 firms in four Kenyan manufacturing sectors observed during 1992-1994.

Variable	*Sample mean*	*Standard deviation*	*Minimum*	*Maximum*
Output	41,688	108,534	4.80	1,150,000
Capital	30,884	128,947	0.16	1,923,077
Wages	3,314	8,141	0.50	94,300
Intermediate inputs	26,089	72,611	1.86	920,647
Firm age (years)	19.5	13.5	2	74.0
Workers (number)	101.6	309.2	1	4000.0
Capacity utilisation	0.63	0.25	0	1.0
Informal firms	26%			

NOTE: Values of output and inputs are expressed in thousands of 1992 Kenyan shillings (1,000 Ksh ≈ 20 USD).

[3] The data on the value of land and buildings of firms are not included in the definition of capital because of a large number of missing values.

[4] Capacity utilisation is defined as 1/(1+C), where C is the percentage increase in output the firms reported to be feasible given the current capital stock. If a firm, for example, can increase output by 100%, capacity utilisation is 50%, and the capital input is 0.5×(replacement cost of machinery and equipment).

[5] This sample consists of 125, 157, 137, and 144 observations for 54, 60, 61, and 60 firms in the food, wood, textile and metal sectors, respectively.

4. Econometric model

To investigate the relationship between age, size and technical efficiency, we employ a stochastic frontier production function, of the type proposed by Battese and Coelli (1995). In this model, a production frontier is specified which defines output as a function of a given set of inputs, together with technical inefficiency effects, which define the degree to which firms fail to reach the frontier because of technical inefficiencies of production. Further, this model specifies that these inefficiency effects are modelled in terms of other observable explanatory variables and all parameters are estimated simultaneously. The stochastic element of this model allows some observations to lie above the production function, which makes the model less vulnerable to the influence of outliers than with deterministic frontier models.

We assume that the frontier technology of firms in the manufacturing sector in Kenya is represented by a translog production function. This functional form is chosen because it is flexible and imposes few restrictions on the data. The stochastic frontier production function is then defined as

$$\ln Y_{it} = \left(\beta_o + \sum_{j=1}^{4} \beta_j x_{jit} + \sum_{j \le k=1}^{4}\sum^{4} \beta_{jk} x_{jit} x_{kit} \right) + v_{it} - u_{it} \tag{3}$$

where the subscripts, i and t, indicate the observation for the i-th firm (i=1,…,N, where N is the number of firms in the sector) in year t (where t=1,2,3 and correspond to 1992, 1993 and 1994, respectively);

$\ln Y_{it}$	represents the natural logarithm of the value of output for the i-th firm in the t-th year;
x_1	represents the natural logarithm of the replacement value of the capital stock, corrected for capacity utilisation;
x_2	represents the natural logarithm of the wages of the firm;
x_3	represents the natural logarithm of intermediate inputs;
x_4	is the time variable;
the v_{it}s	are assumed to be independent and identically distributed normal random variables with mean zero and variance, σ_v^2; and

the u_{it}s are non-negative random variables, which are assumed to be independently distributed, such that u_{it} is the truncation (at zero) of the normal distribution with mean, μ_{it}, and variance, σ^2, where μ_{it} is defined by

$$\begin{aligned}\mu_{it} &= \delta_0 + \delta_1 D_{2it} + \delta_2 D_{3it} + \delta_3 x_{3it} + \delta_4 x_{3it}^2 + \\ &\quad \delta_5 age_{it} + \delta_6 age_{it}^2 + \delta_7 (x_3 \times age)_{it}\end{aligned} \tag{4}$$

where

D_2 is a dummy variable taking the value of 1 in year 2 (i.e., in 1993), and 0 otherwise;

D_3 is a dummy variable taking the value of 1 in year 3 (i.e. in 1994), and 0 otherwise;

age is the natural logarithm of firm age in years.

The terms in the brackets in (3) define the frontier technology for different levels of inputs. Time enters the function to allow for shifts of the frontier over time, which are interpreted as technical change. Deviations from the production function are captured in the two error terms. The v-error accounts for measurement error in outputs and the effects of misspecification in the production technology. The u-error is associated with technical inefficiency of production.

There are several factors that may be captured in the time dummy variables. General effects caused by the macro-economic environment, and general tendencies of efficiency change over time, may be reflected by a common pattern of the sign and magnitude of the coefficients of D_2 and D_3. If sector-specific effects associated with output expansion, as in bakeries, or contraction, as in textiles, are present, these estimates will differ among sectors.

We have chosen to use a production input variable as a proxy for firm size in this study. This approach has previously been adopted by two applications of the stochastic frontier production function on agriculture (Coelli and Battese, 1996; and Ngwenya, Battese and Fleming, 1997), in which farm size was represented by a function of the input land in the inefficiency model. In our specification, we use intermediate inputs, x_3, to represent firm size. The choice of this input variable is motivated by the assumption that its marginal rate of substitution is less than that of capital and wages. Hence the intermediate input variable is a better proxy for size than the other two inputs.

The *logarithm* of firm age is used because an additional year of experience of a firm is expected to have a greater influence on new firms than older ones. Preliminary estimation also suggested that the model with the logarithm of age was a better fit than that with the actual value of age of firms.

The squares and interaction between firm age and size are included to allow for U-shaped and joint relationships between the two variables and technical efficiency. This functional form is more flexible than those employed in the other studies of technical efficiency referred to in Section 2.

The stochastic frontier production model defined by (3) and (4) is estimated separately for each of the four sectors. In addition, a pooled model is estimated which is specified in the same way as the sector models except that it includes intercept shifts of the frontier technology for the different sectors.[6]

Technical efficiency of the i-th firm in the t-th year is defined by

$$TE_{it} = \exp(-u_{it}). \tag{5}$$

Technical efficiency equals one only if a firm has an inefficiency effect equal to zero; otherwise it is less than one.

The parameters of the model defined by (3) and (4) are estimated simultaneously using the computer program, FRONTIER Version 4.1, designed by Coelli (1994), which provides maximum-likelihood estimates of the parameters and predicts technical efficiencies for all firms in the years in which

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6 The corresponding expression to (3) is then

$$\ln Y_{it} = \beta_o + \sum_{j=1}^{4} \beta_j x_{jit} + \sum_{j\leq}^{4} \sum_{k=1}^{4} \beta_{jk} x_{jit} x_{kit} + WOOD_{it} + TEXTILE_{it} + METAL_{it} + v_{it} - u_{it},$$

where WOOD, TEXTILE and METAL are dummy variables which take the value of one if the firm belongs to the corresponding sector, and zero otherwise.

they are observed. The variance parameters are estimated by FRONTIER in terms of $\gamma=\sigma^2/(\sigma^2+\sigma_v^2)$, and $\sigma_S^2=\sigma^2+\sigma_v^2$.

Various tests of hypotheses of the parameters in the frontier function and in the inefficiency model can be performed using the generalised likelihood-ratio test statistic, defined by

$$\lambda = -2\left[\ell\left(H_o\right) - \ell\left(H_1\right)\right] \tag{6}$$

where $\ell\left(H_o\right)$ is the log-likelihood value of a restricted frontier model, as specified by a null hypothesis, H_o; and $\ell\left(H_1\right)$ is the log-likelihood value of the general frontier model under the alternative hypothesis, H_1. This test statistic has approximately a chi-square (or a mixed chi-square) distribution with degrees of freedom equal to the difference between the parameters involved in the null and alternative hypotheses.

If the inefficiency effects are absent from the model, as specified by the null hypothesis, $H_o:\gamma=\delta_0=\ldots=\delta_7=0$, then the statistic, λ, is approximately distributed according to a mixed chi-square distribution. In this case, critical values for the generalised likelihood-ratio test are obtained from Table 1 in Kodde and Palm (1986). If this null hypothesis is true, then the production function is equivalent to the traditional average response function which can be efficiently estimated using ordinary least-squares regression.

Elasticities

Due to the squared and interaction terms on the right-hand side in the translog stochastic frontier production function (3), the elasticities of output with respect to inputs are functions of the levels of the inputs. Since the input variable, intermediate inputs, also appears in the inefficiency model (4), the output elasticity with respect to this input variable is a function of the values of the inputs in both the frontier and the inefficiency models. The general expression for the input elasticity of the *mean output* with respect to the *k*-th input for firm *i* in year *t* is given by (see Battese and Broca, 1997)

$$\frac{\partial \ \ln[E(Y_{it})]}{\partial \ x_k} = \left(\beta_k + 2\beta_{kk}x_{kit} + \sum_{j \neq k}^{4} \beta_{kj}x_{jit}\right) - C_{it}\left(\frac{\partial \ \mu_{it}}{\partial \ x_k}\right), \quad k = 1,2,3 \quad (7)$$

where

$$C_{it} = 1 - \frac{1}{\sigma}\left[\frac{\phi\left(\frac{\mu_{it}}{\sigma} - \sigma\right)}{\Phi\left(\frac{\mu_{it}}{\sigma} - \sigma\right)} - \frac{\phi\left(\frac{\mu_{it}}{\sigma}\right)}{\Phi\left(\frac{\mu_{it}}{\sigma}\right)}\right] \quad (8)$$

and ϕ and Φ are the density and distribution functions of the standard normal variable, respectively. In accordance with Battese and Broca (1997), we refer to the first part of the expression in (7) as the elasticity of frontier output, and to the second part as the elasticity of technical efficiency. The latter part of these two components measures the proportion of the elasticity of mean output which is due to a change in technical inefficiency. Given the specification of our model in (3) and (4), this effect is non-zero only when the *k*-th variable is the intermediate input (k=3). In this case, the elasticity of technical efficiency is

$$-C_{it}\left(\frac{\partial \mu_{it}}{\partial x_3}\right) = -C_{it}\left(\delta_3 + 2\delta_4 x_{3it} + \delta_7 age_{it}\right). \quad (9)$$

We interpret this expression as the elasticity of technical efficiency with respect to firm size. The corresponding elasticity of technical efficiency with respect to firm age is

$$-C_{it}\left(\frac{\partial \mu_{it}}{\partial age}\right) = -C_{it}\left(\delta_5 + 2\delta_6 age_{it} + \delta_7 x_{3it}\right). \quad (10)$$

The elasticities defined by (9) and (10) are evaluated for different size and age categories of firms in the following section in order to analyse the size- and age-efficiency relationships.

Technical change is defined as the partial derivative of $\ln\left[E\left(Y_{it}\right)\right]$ with respect to the time variable x_4. Returns to scale (*RTS*) is defined as the sum of the elasticities of mean output with respect to all inputs. All elasticities are estimated at the means of the explanatory variables.

5. Empirical results

The results obtained from estimating the stochastic frontier production model, including parameter estimates, tests, estimated technical efficiencies and elasticities, are presented in the subsection below. A more detailed analysis of the size-efficiency and the age-efficiency relationships are contained in the following two subsections.

Estimates, tests, and elasticities

The general model, defined by (3) and (4), is estimated for each of the four sectors and for the pooled model using the method of maximum likelihood. The parameter estimates of the stochastic frontier models are presented in Tables 4 and 5. For the translog function, the elasticities of mean output with respect to inputs, firm size and age are functions of subsets of the parameters and the levels of the explanatory variables. Hence the individual coefficients in the stochastic frontier production function are not directly interpretable as elasticities, as for the Cobb-Douglas model.

Several generalised likelihood-ratio tests of null hypotheses involving restrictions on the parameters in both the frontier and the inefficiency models are presented in Table 6. The first two tests consider the frontier function. Given the assumption of the translog stochastic frontier model, Cobb-Douglas technology is rejected in all sectors except wood. This means that input elasticities and substitution relationships are not constant for firms of different sizes and with different values of inputs in these three sectors. The null hypothesis of no technical change, which states that the production frontier does not shift over time, is accepted for all sectors.

The remaining tests in Table 6 consider restrictions on the parameters in the inefficiency model. In all cases, the null hypothesis of no inefficiency effects is rejected. Thus the average response function, in which all firms are assumed to be technically efficient, is not an adequate representation of the data given the assumption of the translog stochastic frontier model.

Table 4. Maximum-likelihood estimates for parameters of translog stochastic frontier production functions for four Kenyan manufacturing sectors.[a]

Variable[b]	Food	Wood	Textile	Metal
Frontier function				
Constant	2.8 (1.5)	8.8 (3.0)	2.94 (0.94)	-0.1 (1.1)
Capital	0.06 (0.30)	-0.27 (0.18)	-0.34 (0.17)	-0.37 (0.13)
Wages	-0.34 (0.53)	0.23 (0.42)	0.72 (0.26)	0.98 (0.40)
Intermediate inputs	0.98 (0.27)	0.34 (0.45)	0.45 (0.28)	0.70 (0.36)
Year	0.37 (0.56)	-1.4 (1.0)	0.33 (0.55)	-0.56 (0.45)
(Capital)^2	0.015 (0.014)	0.003 (0.010)	-0.105 (0.014)	-0.0130 (0.0095)
(Wages)^2	0.130 (0.046)	0.071 (0.033)	0.122 (0.029)	0.060 (0.030)
(Intermediate inputs)^2	0.091 (0.019)	0.073 (0.031)	0.121 (0.029)	0.145 (0.028)
(Year)^2	-0.12 (0.11)	0.07 (0.11)	-0.06 (0.10)	0.021 (0.094)
(Capital)×(Wages)	0.012 (0.047)	0.002 (0.033)	0.026 (0.027)	0.118 (0.031)
(Capital)× (Intermediate inputs)	-0.035 (0.026)	0.008 (0.033)	0.020 (0.034)	-0.049 (0.026)
(Capital)×(Year)	-0.029 (0.049)	0.038 (0.028)	0.020 (0.032)	-0.009 (0.020)
(Wages)× (Intermediate inputs)	-0.200 (0.049)	-0.143 (0.050)	-0.274 (0.050)	-0.275 (0.043)
(Wages)×(Year)	-0.032 (0.064)	0.073 (0.070)	-0.061 (0.042)	0.004 (0.048)
(Intermediate inputs)× (Year)	0.065 (0.044)	-0.037 (0.070)	0.023 (0.051)	0.034 (0.045)
Inefficiency model				
Constant	-4.6 (3.2)	4.1 (1.6)	-2.9 (3.8)	-2.8 (2.4)
D_2 (1993)	3.7 (1.3)	-0.68 (0.35)	0.49 (0.35)	1.53 (0.79)
D_3 (1994)	1.69 (0.85)	0.71 (0.59)	-0.09 (0.53)	-0.58 (0.32)
Intermediate inputs	-0.01 (0.24)	0.26 (0.28)	0.49 (0.70)	1.02 (0.60)
(Intermediate inputs)^2	0.025 (0.015)	-0.035 (0.012)	-0.016 (0.031)	-0.062 (0.038)
age	2.5 (1.3)	-1.47 (0.78)	1.21 (0.68)	-5.4 (1.6)
(age)^2	0.54 (0.30)	0.05 (0.15)	0.22 (0.14)	1.07 (0.73)
(Intermediate inputs)× (age)	-0.42 (0.17)	0.081 (0.053)	-0.169 (0.061)	0.11 (0.27)
Variance parameters				
$\sigma_S^2=\sigma^2+\sigma_v^2$	1.27 (0.36)	0.314 (0.060)	0.299 (0.070)	0.938 (0.088)
$\gamma=\sigma^2/(\sigma^2+\sigma_v^2)$	0.909 (0.034)	0.608 (0.086)	0.740 (0.081)	0.869 (0.014)
Log-likelihood	-75.581	-94.032	-57.376	-79.990
Mean TE	0.765	0.679	0.757	0.800

a Standard errors are given in parentheses under the coefficient estimates, correct to two significant digits.

b All variables in the frontier function and the inefficiency model, except Year and the two dummy variables, are in logarithms, as specified in (3) and (4).

Table 5. Maximum-likelihood estimates for parameters of the translog stochastic frontier production function for the Kenyan manufacturing industry (pooled data).[a]

Frontier model		***Inefficiency model***	
Variable[b]		Variable[b]	
Constant	1.80 (0.87)	*Constant*	-6.7 (3.8)
Capital	-0.110 (0.089)	D_2	1.56 (0.42)
Wages	0.36 (0.17)	D_3	0.40 (0.35)
Intermediate inputs	0.69 (0.16)	*Intermediate inputs*	0.68 (0.42)
Year	0.15 (0.32)	*(Intermediate inputs)*^{2}	-0.011 (0.012)
(Capital)^2	0.0075 (0.0050)	*age*	1.64 (0.87)
(Wages)^2	0.082 (0.017)	*(age)*^{2}	0.33 (0.12)
(Intermediate inputs)^2	0.086 (0.011)	*(Intermediate inputs)×(age)*	-0.270 (0.093)
(Year)^2	-0.085 (0.065)		
(Capital)×(Wages)	0.019 (0.014)		
(Capital)× (Intermediate inputs)	-0.020 (0.012)	***Variance parameters***	
(Capital)×(Year)	-0.000 (0.015)	Variable	
(Wages)× (Intermediate inputs)	-0.174 (0.023)	$\sigma_S^2=\sigma^2+\sigma_v^2$	0.91 (0.21)
(Wages)×(Year)	-0.012 (0.026)	$\gamma=\sigma^2/(\sigma^2+\sigma_v^2)$	0.853 (0.039)
(Intermediate inputs)× (Year)	0.022 (0.023)		
WOOD	0.023 (0.061)		
TEXTILE	-0.055 (0.062)	*Log-likelihood*	-367.886
METAL	-0.019 (0.060)	*Mean TE*	0.768

a., b.: See Table 4.

The estimates of the γ-parameter range between 0.608 and 0.909, which implies that a substantial proportion of the total variability is associated with inefficiency of production.

The last four tests of hypotheses in Table 6 involve restrictions on the age, size and year parameters in the inefficiency models. The results differ among sectors, which makes the issue of pooling data from the four sectors important. The joint test of no age and size effects is accepted in the food and metal sectors, but rejected in the wood and textile sectors. When the age and size effects are tested individually, size is significant in both the textile and the wood sectors, while age is significant only in the textile sector. In the pooled model, size, but not age, is significant at the 10% level. The joint test of age and size is significant at the 10% level. These tests indicate that there exist a significant size-efficiency relationship in at least two, and a significant age-efficiency relationship in at least one, of the four sectors, given the specifications of the stochastic frontier production functions. The directions and magnitudes of these age and size effects are discussed in the following two subsections.

Table 6. Generalised likelihood-ratio tests of null hypotheses for parameters in the stochastic frontier production function for the sectors of Kenyan manufacturing.

Null Hypothesis, H_0	Model					Critical
	Food	Wood	Textile	Metal	Pooled	value
$\beta_{ij}=0$ i,j=1,2,3,4 (Cobb-Douglas)	45.24*	15.14	62.55*	27.59*	90.47*	18.31
$\beta_4=\beta_{j4}=0$ j=1,2,3,4 (no technical change)	3.17	5.45	7.49	5.41	4.27	11.07
$\gamma=\delta_0=\delta_1=\ldots=\delta_7=0$ (no inefficiency effects)	38.66*	18.09*	32.93*	17.84*	21.85*	16.27
$\delta_3=\delta_4=\delta_5=\delta_6=\delta_7=0$, (no age and size effects)	3.07	17.56*	26.21*	6.26	10.22#	11.07
$\delta_3=\delta_4=\delta_7=0$, (no size effects)	0.30	14.65*	23.79*	5.34	7.62#	7.81
$\delta_5=\delta_6=\delta_7=0$, (no age effects)	2.27	4.48	9.67*	5.47	4.61	7.81
$\delta_1=\delta_2=0$, (no time effects)	4.47	3.65	3.71	2.12	11.08*	5.99

NOTE: Values of the generalised likelihood-ratio statistic are given in the body of the table. Values which exceed the critical value in the table are significant at the 5%-level and are marked by an asterisk (*). Values that are significant at the 10%-level are marked by (#).

These results are, however, sensitive to the choice of size proxy and to the inclusion of the smallest firms in the sample. When the intermediate-inputs variable, x_3, was substituted for the logarithm of the number of workers as a proxy for size in the inefficiency model, the size effect became insignificant in the pooled model. In the estimations of the separate sectors, however, the results are approximately the same for all sectors except wood where size is insignificant. This underlines the crucial importance of the definition of firm size in studies of this kind.

According to Liedholm and Mead (1987) the accuracy of data on flow variables is particularly bad for the smallest firms in developing countries. The models were therefore re-estimated omitting firms with less than 10 workers. In the pooled model, the effect of size is still significant at the 10% level. In the estimations of the separate sectors, the parameters became unstable and very sensitive to changes in start values for the iterative procedure for maximisation of the likelihood function. Size and age became insignificant in all sectors. This may possibly be an effect of the small sample sizes[7] in combination with some sample noise in the data.

The null hypothesis of no time effects is accepted in all sector models, but not in the pooled model which suggests a drop in technical efficiency in 1993 compared with 1992 and 1994. Referring to Table 2, this result may indicate that macro-economic indicators, such as inflation and GDP growth, have some influence on the technical efficiency of firms.

Because the variables used in the sector and pooled models are the same, we are able to test the hypothesis that the parameters are equal among the sectors. This test is rejected[8], which indicates that pooling is not appropriate, given the sector-wise models.

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[7] After omitting firms with less than 10 workers, there remain 101, 60, 77, and 87 observations for 46, 40, 35, and 41 firms in the food, wood, textile and metal sectors, respectively.

[8] The test is performed using equation (6) where $\ell(H_o)$ is the value of log-likelihood function for the pooled model and $\ell(H_1)$ is the sum of the values of the log-likelihood functions for the four sector models. The test statistic is equal to 121.81, well above the 5% level critical value of 92.8 (df=72).

The technical efficiencies for the sample firms in the four Kenyan manufacturing sectors are predicted for each year observed. Histograms of these efficiencies are displayed in Figures 1 and 2.

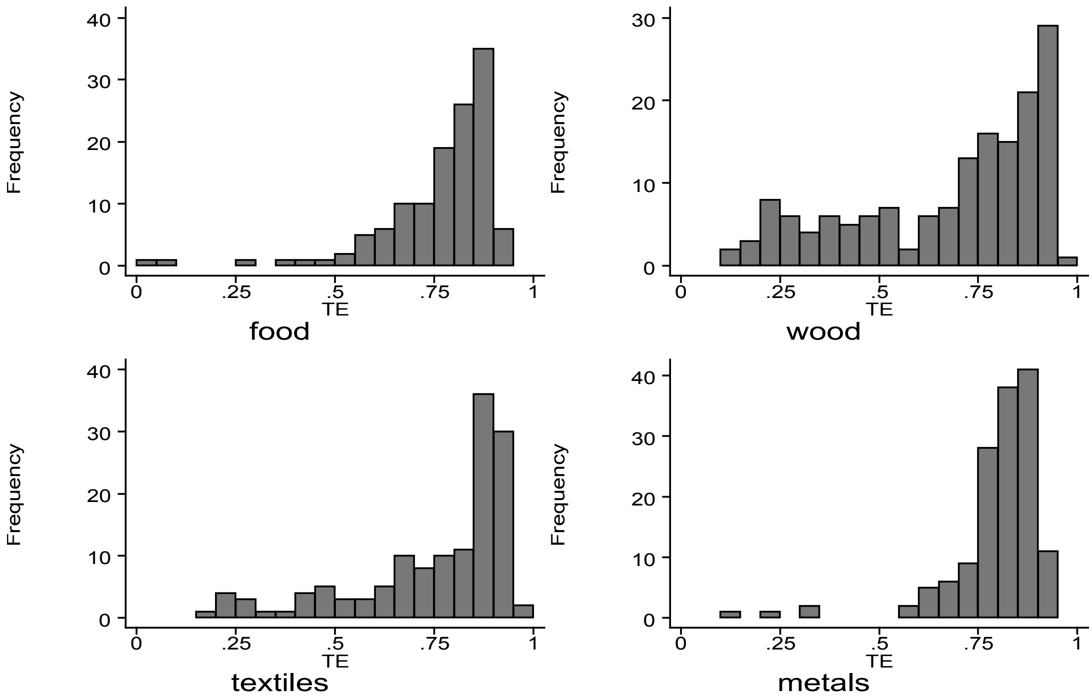

Figure 1. Distributions of technical efficiencies for Kenyan manufacturing firms in the sector models.

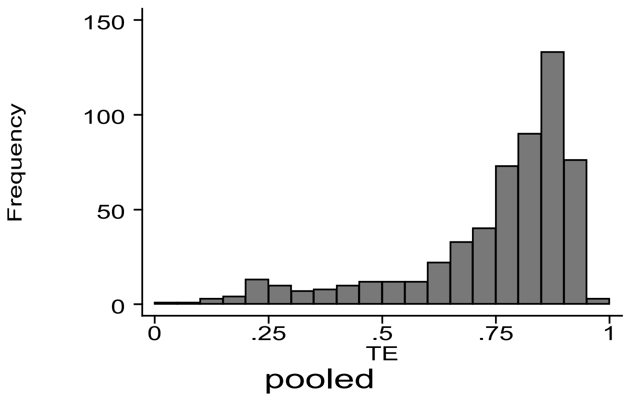

Figure 2. Distribution of technical efficiencies for Kenyan manufacturing firms in the pooled model.

The distributions of the technical efficiencies of the firms are negatively skewed, especially in the wood and textile sectors, in which a relatively large number of firms are operating at low levels of technical efficiency. The distribution of technical efficiencies in the pooled model appears less dispersed than the distributions of the four sectors estimated separately.

Elasticities of mean output with respect to the three input variables are estimated in Table 7 at the mean values of the variables involved. The elasticity for intermediate inputs is higher than the capital and wage elasticities, as expected, given the low level of capacity utilisation. Because capital and wages are stock and flow input variables, respectively, their elasticities are not directly comparable. The estimate for capital elasticity in the textile sector is considerably lower than in the metal sector, which suggests that the technologies between these sectors are different. The elasticities for wages and intermediate inputs differ little among sectors. The returns to scale are close to unity in all models. In the textile sector, the estimate for technical change is negative, showing that the dramatic output decrease in this sector may have been associated with an inward shift of the production frontier. The estimated values for technical change are not significantly different from zero, which is consistent with the conclusion of no technical change reported in Table 6.

Table 7. Input elasticities and technical change estimated at the mean of the input levels.

Variable	Food	Wood	Textile	Metal	Pooled model
Capital	0.079	0.073	0.042	0.099	0.094
	(0.056)	(0.043)	(0.052)	(0.039)	(0.022)
Wages	0.202	0.173	0.213	0.148	0.176
	(0.058)	(0.068)	(0.052)	(0.064)	(0.031)
Intermediate inputs	0.725	0.693	0.731	0.765	0.729
	(0.058)	(0.068)	(0.062)	(0.063)	(0.028)
Returns to scale	1.007	0.939	0.986	1.011	0.999
	(0.038)	(0.039)	(0.033)	(0.025)	(0.020)
Technical change	0.040	-0.034	-0.102	0.004	0.012
	(0.070)	(0.076)	(0.068)	(0.048)	(0.038)

NOTE: Standard errors are given in parentheses under the coefficient estimates, correct to two significant digits.

Given the standard errors of the estimates in Table 7, all differences of the estimated elasticities at the mean values are insignificant. The main difference between the sector-wise and the pooled models appears to be the estimated standard errors, which are notably lower in the pooled model. Thus, the effects of pooling with regard to estimated input elasticities evaluated at the sample means seem to be rather small, although some improvement in terms of precision of the estimates is gained.

Firm size and technical efficiency

To obtain a first indication of the size-efficiency relationship, the sample firms were categorised according to size and then the mean technical efficiencies were estimated. The definitions of these categories are presented in Table 8 and mean efficiencies in Table 9.[9] In the wood and textile sectors, technical efficiency increases uniformly with size. The same pattern occurs in the pooled model. In the food and metal sectors, the largest size groups are the most efficient, whereas the other size categories do not exhibit any regular pattern. The overall impression, however, is that technical efficiency increases with firm size.

Table 8. Definitions of size categories of firms.

Size category	Intermediate input interval in thousands of KSh	Mean number of workers	Number of firms	Mean firm age in years
very small	0 - 150	4.2	109	15.3
small	150 - 1,000	9.8	115	15.5
medium	1,000 - 5,000	34.6	105	23.8
large	5,000 - 30,000	94.5	135	18.6
very large	30,000 +	395.3	99	25.4

Table 9. Mean technical efficiencies by sector and size categories.

Size category	Food	Wood	Textile	Metal	Pooled model
very small	0.68	0.42	0.56	0.76	0.68
small	0.67	0.53	0.71	0.80	0.72
medium	0.78	0.77	0.83	0.77	0.79
large	0.76	0.88	0.90	0.80	0.81
very large	0.81	0.93	0.91	0.87	0.84
All intervals	0.76	0.68	0.76	0.80	0.77

[9] Direct comparisons among sectors are of limited usefulness because efficiency levels are based on sector-specific frontier production functions.

The elasticities of technical efficiency with respect to firm size, presented in Table 10, support this finding. The signs are positive in all models and in all size intervals when estimated at the sample means, which indicates that there exists a positive relationship between firm size and technical efficiency. In addition, this effect becomes weaker for every larger size category of firms in all sectors except for metals. Hence, the positive size-efficiency relationship seems to be stronger for small than for large firms.

The strongest size-efficiency relationship resides in the wood sector, followed by textiles. This is consistent with the fact that the size effects are individually significant only in these two sectors. Nevertheless, the standard errors of the elasticity estimates in Table 10 suggest that the size effects are also significant for several size categories in the food and metal sectors. Hence, a size-efficiency relationship may exist in all four sectors which conflicts with some of the results obtained using the generalised likelihood ratio tests above.

Table 10. Elasticities of technical efficiency with respect to firm size, evaluated at the means of the inputs for different size categories.

Size category	Food	Wood	Textile	Metal	Pooled model
very small	0.061 (0.021)	0.240 (0.099)	0.159 (0.030)	0.006 (0.017)	0.0389 (0.0089)
small	0.0219 (0.0086)	0.240 (0.051)	0.134 (0.038)	0.0177 (0.0068)	0.0326 (0.0082)
medium	0.0210 (0.0076)	0.089 (0.016)	0.057 (0.022)	0.0286 (0.0079)	0.0298 (0.0089)
large	0.0173 (0.0073)	0.0392 (0.0060)	0.025 (0.014)	0.0280 (0.0042)	0.0214 (0.0074)
very large	0.0108 (0.0052)	0.0168 (0.0030)	0.014 (0.010)	0.0237 (0.0047)	0.0153 (0.0059)
All intervals	0.0115 (0.0057)	0.0414 (0.0065)	0.025 (0.014)	0.0225 (0.0041)	0.0193 (0.0070)

NOTE: Standard errors are given in parentheses under the coefficient estimates, correct to two significant digits.

Although Table 10 illustrates how the size-efficiency relationship changes over the size spectrum, it is silent on how firm age influences this elasticity. Most importantly, if the size effect is heavily dependent on firm age, the results in Table 9 do not rule out the possibility that the elasticity switches sign as the age variable is scaled up or down.

To investigate the sign of the size-efficiency effect for all observations, we need to evaluate the partial derivative of the mean of the inefficiency effects, μ_{it}, in (4) with respect to size, which is given by

$$\frac{\partial \mu_{it}}{\partial x_3} = \delta_3 + 2\delta_4 x_{3it} + \delta_7 age_{it} . \qquad (11)$$

The sign of this derivative depends not only on the sign on the parameters involved, but also on the values of the age and size variables. In fact, the expression in (11) shows that the marginal effect of size is a linear function of size and age. By setting the derivative in (11) to zero and solving for x_3, we obtain

$$x_3 = -\frac{\delta_3 + \delta_7 age_{it}}{2\delta_4} \qquad (12)$$

which is a straight line in the size-age space. This line defines the set of combinations of age and size for which the marginal effect of size on technical inefficiency is zero. On one side of the line, the effect of size is either positive or negative, depending on whether (12) defines a minimum or a maximum value.

In Figure 3, the size-age values for the sample firms in the four sectors are plotted together with lines defined by (12). The slopes of the lines vary considerably among the plots, which suggests that the sectors are heterogeneous. In all sectors, an overwhelming majority of firms are on that side of the line where the marginal effect of size on technical inefficiency is negative, which implies that the size-efficiency relationship is positive. In the wood and textile sectors, the only sectors where the parameter estimates involved are significant, size has a positive impact on efficiency in all firms but one. A small number of firms in the food and metal sectors, however, exhibit a negative size-efficiency relationship. These firms are very different in terms of both age and size characteristics between the two sectors; while they are young and of all sizes in the food sector, they are comparably old and of small size in the metal sector.

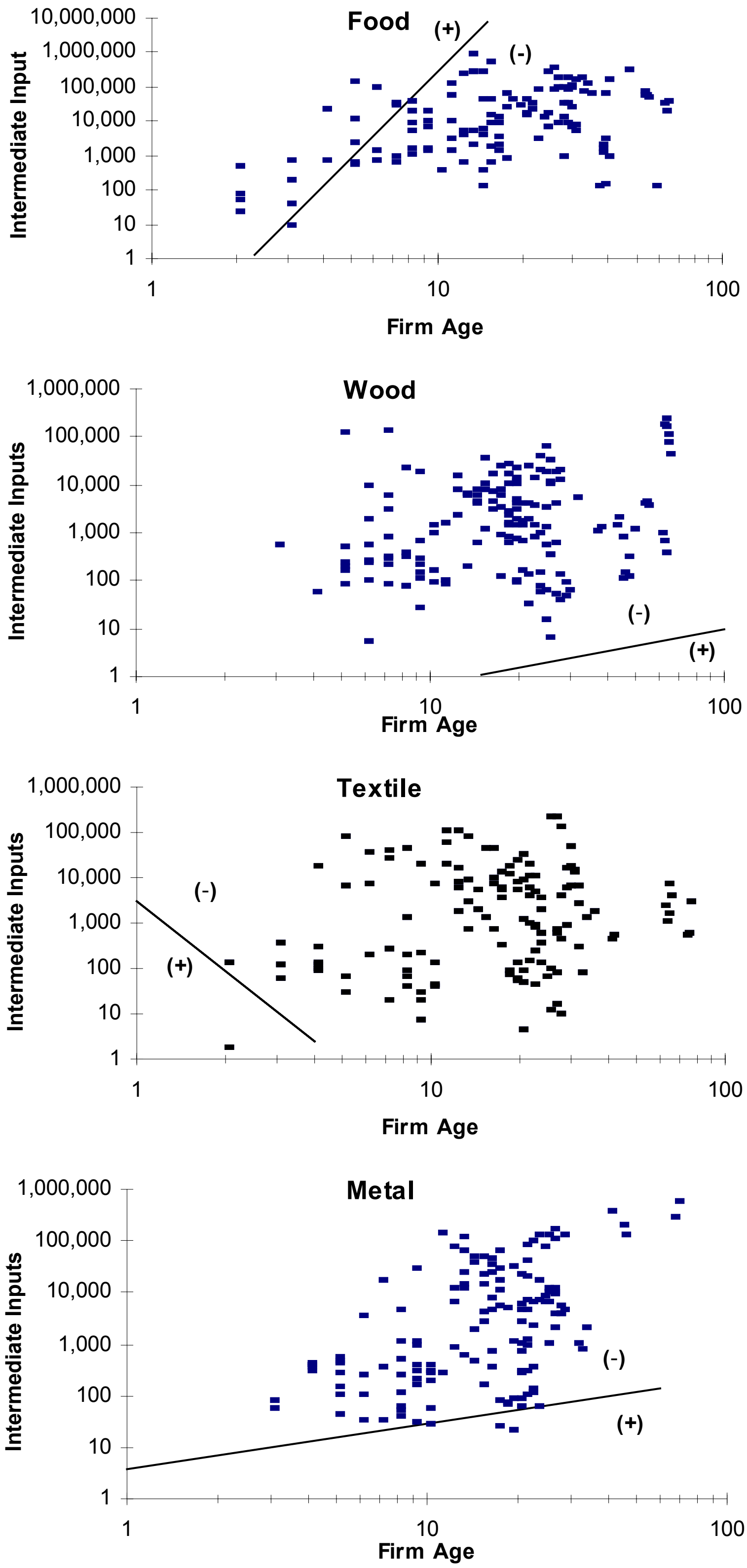

Figure 3. The marginal effect of firm size on technical inefficiency (sector models).

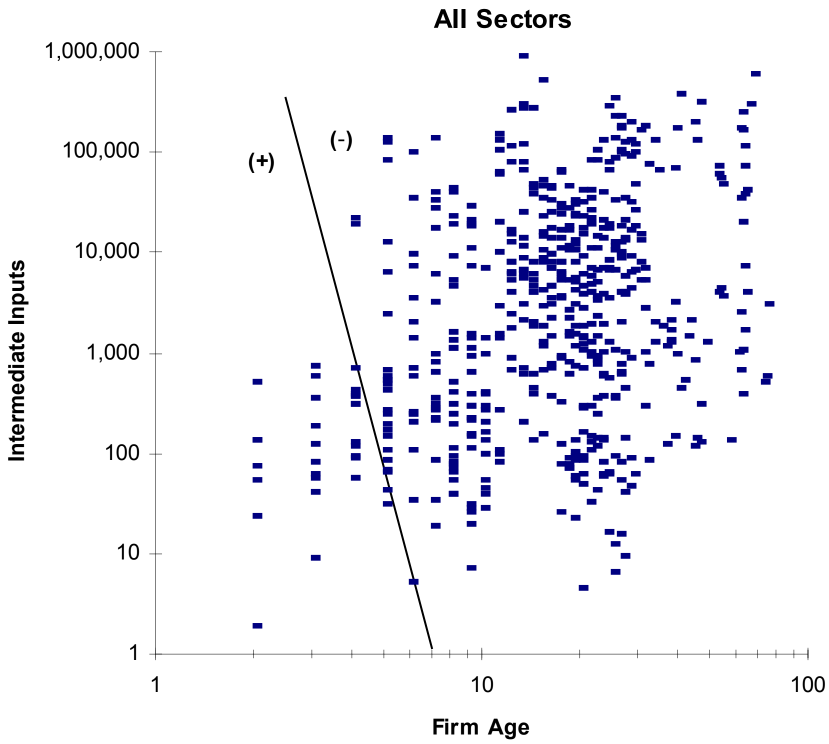

Figure 4. The marginal effect of firm size on technical inefficiency (pooled model).

The plot for the pooled model in Figure 4, resembles that of the food sector but has an even steeper slope of the line. We may interpret this as an indication of a strong impact of firm age on the size-efficiency relationship. More precisely, the marginal effect of size on technical efficiency is positive for almost all firms above five years of age and negative for all firms below that age.

The influence of age on the size-efficiency relationship in the pooled model is further illustrated by the estimates in Table 11, which presents elasticities of technical efficiency with respect to size evaluated for different age categories. The elasticity is negative for firms in the one to four year range, but becomes positive and gradually stronger for older firms.[10] As indicated by the standard

[10] This pattern is not present in the other two sectors where the size effects are significant, wood and textiles. Only two firms in the wood sector, and eleven in the textile sector, are, however, in the one-to-four-year age interval.

errors, however, the size-efficiency effects may not be significant for firms in the 1-4 and 5-10 year intervals.

Table 11. Elasticities of technical efficiency with respect to firm size in the pooled model, evaluated at the means of the inputs for different age intervals.

Age interval in years	Number of firms	Mean number of workers	Elasticity of technical efficiency: coefficient	Elasticity of technical efficiency: standard error
1 – 4	31	16.5	-0.0087	0.0129
5 – 10	125	28.2	0.0172	0.0078
11 – 20	191	98.0	0.0186	0.0070
21 – 30	146	124.1	0.0194	0.0069
30 +	69	235.1	0.0185	0.0065
All intervals	563	102.2	0.0193	0.0070

Firm age and technical efficiency

As shown by the hypotheses tests above, the effect of age on technical efficiency is less significant than the effect of size. Whereas the size-efficiency relationship is significant in the pooled model and in two of the four sectors, the impact of age is insignificant in the pooled model and in all sectors except textiles.

The elasticities of technical efficiency with respect to age for different size categories are reported in Table 12. No uniform pattern is visible in the age-efficiency relationship across sectors and size categories. In the textile sector and in the pooled model, the elasticity is negative for the three smallest size categories and positive for the two largest. Such a shift in sign also occurs in the wood sector, but with reversed sign, so that the age-efficiency relationship is positive for small firms and negative for large firms. In the food sector, the age-efficiency relationship is positive for all sizes, except for the smallest category of firms, whereas in the metal sector the elasticity is negative in all size categories.

Table 12. Elasticities of technical efficiency with respect to firm age, evaluated at the means of the explanatory variables.

Size category	Food	Wood	Textile	Metal	Pooled model
very small	-0.086 (0.047)	0.23 (0.13)	-0.236 (0.087)	-0.079 (0.059)	-0.053 (0.021)
small	0.045 (0.030)	0.083 (0.063)	-0.109 (0.055)	-0.067 (0.026)	0.008 (0.011)
medium	0.021 (0.016)	-0.005 (0.030)	-0.027 (0.023)	-0.151 (0.043)	0.015 (0.012)
large	0.024 (0.050)	-0.008 (0.013)	0.011 (0.010)	-0.109 (0.024)	0.039 (0.016)
very large	0.045 (0.020)	-0.0087 (0.0074)	0.0159 (0.0080)	-0.089 (0.020)	0.032 (0.013)
All intervals	0.053 (0.024)	-0.009 (0.014)	0.0103 (0.0095)	-0.072 (0.019)	0.039 (0.016)

NOTE: Standard errors are given in parentheses under the coefficient estimates, correct to two significant digits.

To determine the direction of the marginal effect of age on technical inefficiency, a comparable analysis to that in the subsection above is performed in Figures 5 and 6. Here, the straight lines define the size-age combinations for which the age effects are zero. In all sectors, the age-efficiency relationship is positive for some firms and negative for others. In the textile sector, the only model in which the involved coefficients are significant at the 5% level, the age-efficiency relationship is positive for large and young firms, and negative for small and older firms. This tendency is also present in the pooled case, although the age effects are insignificant in that model.

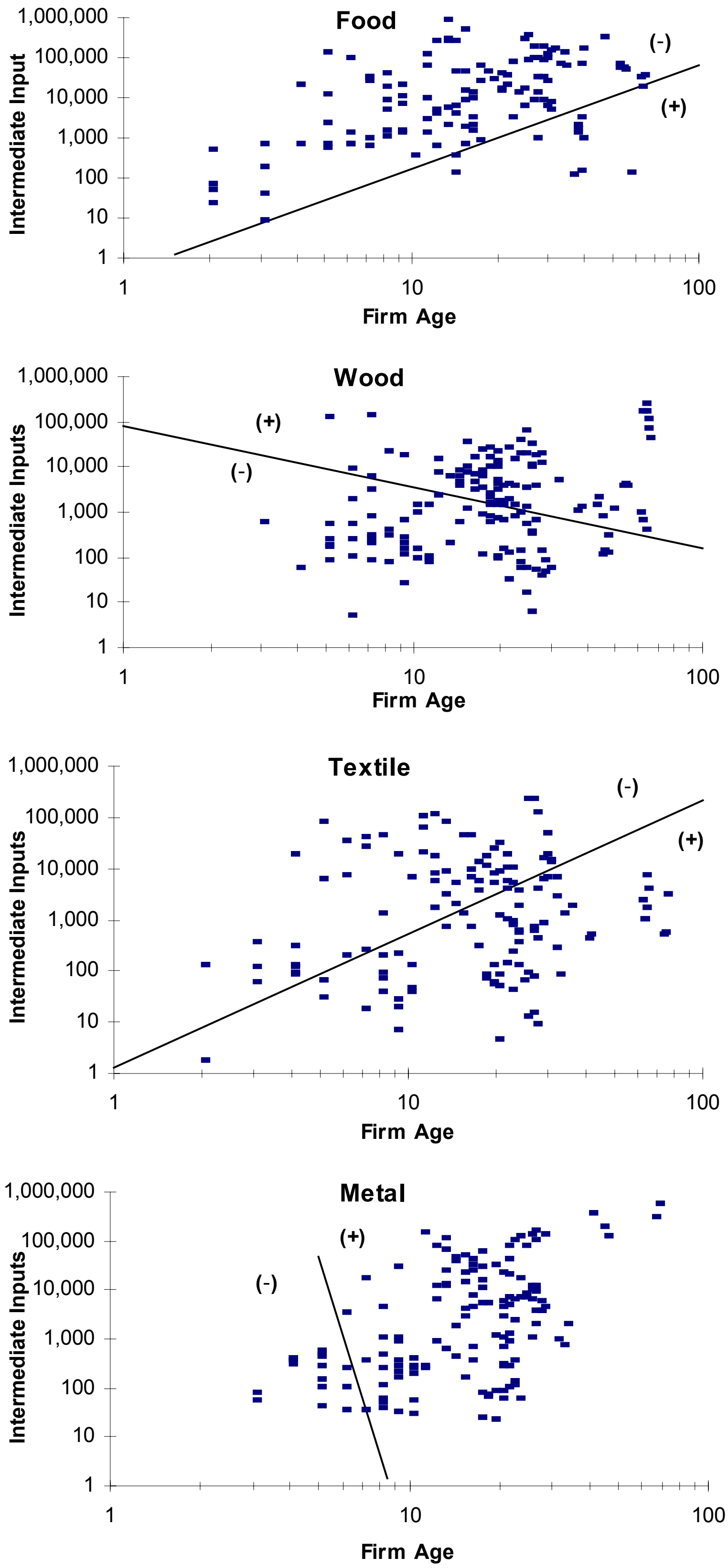

Figure 5. The marginal effect of firm age on technical inefficiency (sector models).

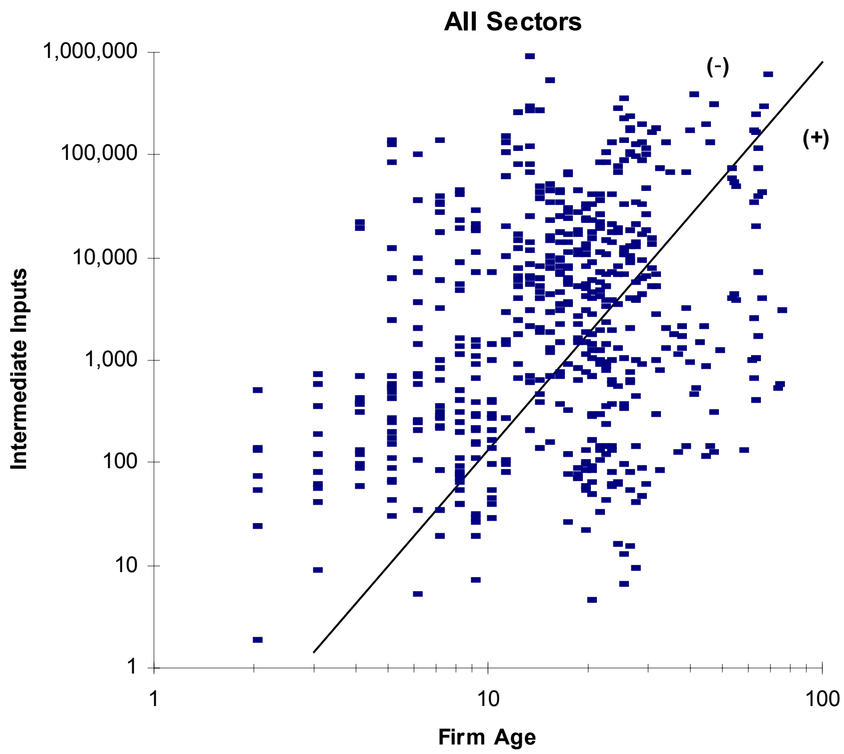

Figure 6. The marginal effect of firm age on technical inefficiency (pooled model).

6. Summary and conclusions

This paper explores the relationships between technical efficiency and firm size, and between technical efficiency and firm age, in four Kenyan manufacturing sectors using stochastic frontier production function models. The estimations reveal some degree of heterogeneity among the sectors. A test of the null hypothesis that the parameters in the stochastic frontier production models are the same for the four sectors, is rejected, which implies that technology, as well as the relationship between age-size and technical efficiency may differ across sectors. This finding is consistent with other studies of manufacturing sectors in developing countries, and emphasises the importance to identify appropriate levels of aggregation for analyses of this kind.

Another finding is that the mean technical efficiency generally increases with size in all sectors when size is defined as the value of intermediate inputs.

In the textile and wood sectors, size has an individual and significant effect at the 5% level on technical efficiency, and the effect is stronger for small than for large firms. The size effect is significant at the 10% level in the pooled model where the interaction between age and size plays a very interesting role. It is shown that the marginal effect of size may be negative for firms up to four or five years of age. Thereafter it becomes positive and stronger as firms get older.

Age has a less systematic impact on technical efficiency than firm size. In textiles, which is the only sector model with significant age effects, the age-efficiency relationship is negative for small and old firms, but positive for large and young firms.

It should be noted that these results are sensitive to the definition of firm size and to the inclusion of the smallest firms. When the number of workers was used as a size proxy, the size effects are only significant in the textile sector. The impact of omitting firms with less than ten workers is also noteworthy. In the pooled model, the effects are still significant at the 10% level when the smaller firms are excluded. In the separate sector models, the parameters of the stochastic frontier production functions become unstable, and all age and size effects are insignificant, which possibly is an effect of small sample sizes in combination with noise in the data.

The empirical evidence presented here is broadly consistent with a positive size-efficiency relationship, but not with a positive age-efficiency relationship, as proposed by Jovanovic (1982). The evidence suggests that the correlation between age and efficiency may be both positive and negative, depending on firm size and sector of the industry. This suggests that more than a selection process is reflected in the age variable. Such effects may include, for example, the gains from a growing stock of experience, and, the losses from a capital stock that becomes obsolete. Hence, the direction of causality in the age-efficiency relationship may go both ways: it runs from efficiency to mean age of firms in the selection process, and from age to efficiency in the learning-by-doing and capital-depreciation processes. The age variable will obviously pick up the combined effect of these factors, which makes it conceptually hard to interpret.

Although the evidence does not support any direct effect of age, it may nevertheless have an indirect influence. As proposed by the pooled model, the size-efficiency relationship is not positive and significant until the firms have reached some maturation age. This finding has no normative implication for policy if the Jovanovic assumption, that efficiency determines firm size, is true. If, on the other hand, causality goes both ways also in the size-efficiency relationship, so that firms may improve their efficiency by becoming larger, then this finding implies that entrants cannot improve efficiency by growing until they have reached a certain age threshold. In other words, firms do not learn over time how to become more efficient, as is the predominant consensus advocated by Tybout and Roberts (1997) and others. Rather, firms learn how to improve efficiency by growing.

For policy considerations in Kenya and other Sub-Saharan countries, this study suggests that one of the main reasons for technical inefficiency in manufacturing sectors is because of the large number of small firms. If it is true that size may improve technical efficiency, then support programmes for private firms should be designed in order to provide a business environment which stimulates growth in size, rather than in number, of small firms.

Furthermore, if it is true that size does not improve efficiency until the firms have reached some threshold age, then the scope for size-driven improvements in technical efficiency may be reduced by high turnover rates in an industry. Apart from the positive effects of high entry and exit rates in manufacturing industries in developing countries, in terms of selection and survival of the most efficient firms, high turnover may also have a negative effect in that it reduces the space for an overall improvement in technical efficiency through firm growth.

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Appendix: Deflators for Output, Capital and Wages

During the years when the data were collected, Kenya experienced large fluctuations in price and output levels. All input and output variables were deflated to real values. Three different deflators were used, including a capital deflator, a wage deflator and an output deflator. The output deflator was also used for the intermediate inputs x_3. The wage and capital deflators were assumed to be the same for the different sectors, while the output deflators varied among the sectors. In the food sector, two deflators were used, one for bakeries and another for "total food manufacturing" to account for the unique drop in price for bakery products in 1994.

The deflators were calculated using information from Central Bureau of Statistics (1995) and are presented in Table A.

Table A. Output and input deflators

Deflators (1992=100)	Year		
	1992	1993	1994
Output deflators by sector:			
Food (Total food manufacturing)	100	135	166
Food (Bakery products)	100	137	109
Wood (Furniture and fixtures)	100	122	146
Textiles	100	127	209
Metal	100	132	145
Capital deflator	100	123	165
Wage deflator	100	114	134
CPI deflator	100	146	188

The output deflators were calculated as $p_t=(pq)_t/q_t$ (t=1992, 1993, 1994), where $(pq)_t$ is output by sector (Table 94c), and q_t is the quantity index (Table 92). The resulting index series p_t was then divided by p_{92}, which defines 1992 as the base year.

The capital deflator is calculated using the data on capital formation of private machines and equipment in the manufacturing sector which are reported in current and fixed prices in Central Bureau of Statistics (1995) (Table 43a-b).

The wage cost deflator was calculated using p_t/p_{92} (t=1993, 1994) where p denotes monthly average earnings per full-time employee. The index illustrates how nominal wages behaved during the years of study. By comparing this index with the CPI, it is evident that wages did not keep pace with inflation. Using the CPI as a deflator for wages thus introduces a downward bias in the labour input.

A NOTE ON HOW TO 'EXPLAIN' TECHNICAL EFFICIENCY IN SFA AND DEA MODELS:

An empirical example using Kenyan data[#]

Karl Lundvall*

May 1999

Abstract: Technical efficiency is estimated for a panel of Kenyan firms using data envelopment analysis (DEA) and regressed in a second step on age and size using various models. Size exhibits a positive association with efficiency whereas age does not, which is broadly consistent with the results from a stochastic frontier production function analysis (SFA) of another study. Depending on model, mean efficiency ranges between 0.38 and 0.54, compared to 0.68-0.80 in SFA, and the correlation coefficients between DEA- and SFA-efficiencies are 0.39-0.61. Differences between the approaches and specification issues for second-step analysis of DEA efficiency scores are discussed.

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1. Introduction

A central element in the productivity literature is the concept of a best-practise production frontier, which identifies maximum output given inputs (or minimum inputs given outputs). A deviation from the frontier means that the unit is producing less than it is technologically able to, implying some degree of technical inefficiency. During the last twenty years or so, much effort has been devoted to the development of methods to estimate such frontiers and the literature is rich in both theoretical and empirical contributions. Less attention, at least at more theoretical levels, has been given to the natural second step: i. e. to model predicted efficiencies in terms of background variables. Indeed, there exists no well-grounded methodological framework to analyse the determinants of efficiency, possibly because of the difficulties involved. These include the tricky distinction of factors assumed to affect *either* output *or* efficiency, the potential presence of correlation between the explanatory variables in the frontier and efficiency models; and the atypical distribution of the efficiency variable that is the (0,1]-interval with a mass point at one.

Some of the econometric applications have adopted a two-stage procedure to analyse the determinants of efficiency, in which the first stage involves estimation of a stochastic frontier production function and prediction of efficiency scores. As a second step, these scores are used as a dependent variable and regressed on a set of variables believed to influence efficiency. A difficulty with this approach, in addition to those just mentioned, is that efficiency scores commonly are assumed independently distributed in the frontier estimation, which is in contradiction to its being modelled in a second step as a function of other variables (Battese and Coelli 1993). Within the econometric approach to efficiency measurement, models have been proposed to overcome this problem through simultaneous estimation of a stochastic frontier production function and a model of efficiency (Battese and Coelli, 1993 and 1995, Reifscheider and Stevenson 1991, Huang and Liu 1994).

These latter models are elegant in that they accommodate statistical noise, thereby allowing an occasional observation to lie above the frontier, and also enable consistent analysis of the efficiency determinants. Nevertheless, they rest on a number of assumptions regarding the functional form of the production technology, and the distributions of the errors and efficiencies that are hard or even impossible to explicitly test for. Further, it has been shown that stochastic frontier models are sensitive to heteroscedasticity (Caudill and Ford 1993). Convergence to global maximums of the likelihood functions can also be hard to achieve. The applied researcher may therefore opt for an alternative methodology to examine whether her stochastic frontier results are robust. Data Envelopment Analysis (DEA) is a natural candidate for such an alternative model. Compared to the econometric stochastic frontier approach (SFA), it is non-parametric, hence avoiding the risk of misspecification, but also deterministic, which implies that noise, should it exist, may feed directly into the efficiency estimates. Given its different set of assumptions, performing a second-stage analysis on DEA efficiencies is probably less dubious conceptually than it is to perform it to an SFA-model, although some of the problems above are likely to remain.

In any case, it is argued here that applying both methods may be useful, and that is exactly what I am about to do in this paper. Specifically, the purpose of the paper is to employ DEA and to model the efficiencies in a second step in terms of firm age and size using different regression techniques. The data is drawn from a survey of Kenyan manufacturing firms in four sectors (food, wood, textiles and metals) observed during 1992-94. The results will be compared with those of a SFA-study on the same issue that I conducted with George Battese (Lundvall and Battese, 1998, hereafter LB). In that paper, a significant positive size-efficiency relationship was detected in the pooled and in two of the four sector models (wood and textiles). Firm age had no significant association with efficiency except in textiles.

In what follows, I briefly outline in section 2 the specifications of the SFA- and DEA-models employed. Section 3 shortly presents the data before the results are discussed in section 4. Section 5 concludes.

2. Models

SFA and DEA are the main analytical methodologies in use today for the measurement of productive efficiency, and have been developed side-by-side since the 1970s. Extensive surveys of SFA include, for instance, Schmidt (1985-86) and Greene (1993). For DEA, there are recent books by Charnes *et al* (1994) and by Färe and Grosskopf (1996).

The SFA-model

SFA involves estimation of a specified functional relationship between observed output and inputs, which can be expressed as

$$y_{it} = f(x_{it};\beta)\exp\{v_{ti} - u_{it}\}, \tag{1}$$

where y_{it} is output; x_{it} a vector of inputs with an associated parameter vector β; v_{it} a random disturbance term assumed *iid* $N(0, \sigma_v^2)$, and; u_{it}, a non-negative random term distributed independently of v_{it}. The indices $i=1,\dots,N$ and $t=1,\dots,T$ refer to the firm and period of the observation. Potential output, given a bundle of inputs, is defined by the frontier production function $f(\cdot)$, which can be of Cobb-Douglas, translog or some other functional form. Firm-level deviations from the frontier are either due to statistical noise, captured in the v-variable, or to technical inefficiency of production, which is reflected in the u-variable. The level of technical efficiency of a firm is defined as $TE_{it} = \exp(-u_{it})$ and corresponds to the ratio of observed to potential output given inputs. The measure equals one for firms operating on the frontier ($u_{it} = 0$), and between one and zero for firms with some degree ($u_{it} > 0$) of technical inefficiency in production.

The SFA-model estimated in LB is due to Battese and Coelli (1993) and assumes u_{it} to be distributed according to a normal distribution truncated at zero, with mean μ_{it} and variance σ^2. The production function is specified according to the translog functional forms using capital, wages, intermediates and time as inputs. The mean of the inefficiency effects, μ_{it}, is defined as

$$\mu_{it} = g(Z_{it};\delta), \tag{2}$$

where Z_{it} is a vector of determinants for efficiency including age and size expressed in logs, and δ is the associated vector of parameters. The elasticity of technical efficiency with respect to size in this particular model is (Battese and Broca, 1997)

$$\frac{\partial \ln TE_{it}}{\partial \ln size} = -C_{it}\left(\frac{\partial \mu_{it}}{\partial \ln size}\right), \tag{3}$$

where

$$C_{it} = 1 - \frac{1}{\sigma}\left[\frac{\phi(\mu_{it}/\sigma - \sigma)}{\Phi(\mu_{it}/\sigma - \sigma)} - \frac{\phi(\mu_{it}/\sigma)}{\Phi(\mu_{it}/\sigma)}\right].$$

The expression for the age elasticity is derived in the same way. Estimates of both size and age elasticities are reported in LB, and are interpreted as the percentage change in efficiency induced by a percentage change in size or age. To accomplish consistence with the second-stage DEA-model, however, we wish to redefine these elasticities to their semi-log counterparts, interpreted as the *unit*-change in technical efficiency given a percentage change in size. These are defined as

$$\frac{\partial TE_{it}}{\partial \ln size} = \frac{\partial \ln TE_{it}}{\partial \ln size} \cdot TE_{it} = \left\{-C_{it}\left(\frac{\partial \mu_{it}}{\partial \ln size}\right)\right\} \cdot TE_{it}. \tag{4}$$

We refer to (4) as the marginal effect of technical efficiency with respect to size. The corresponding expression for the age-effects is derived and interpreted accordingly.

The main advantages of the SFA-model is its capacity to accommodate statistical noise, such as measurement error, and its parametric specification of the technology which permits evaluation of various aspects of the production process. DEA does not share these virtues. On the other hand, it does not require assumptions regarding functional forms and efficiency distributions.

The DEA-model

In DEA, the production frontier is constructed by combining the data points for the best-practise firms in the output-input space with planes or hyper-planes. For the one-output one-input case, the frontier is constructed by line segments and can be illustrated in a two-dimensional graph, as in Figure 1 below.

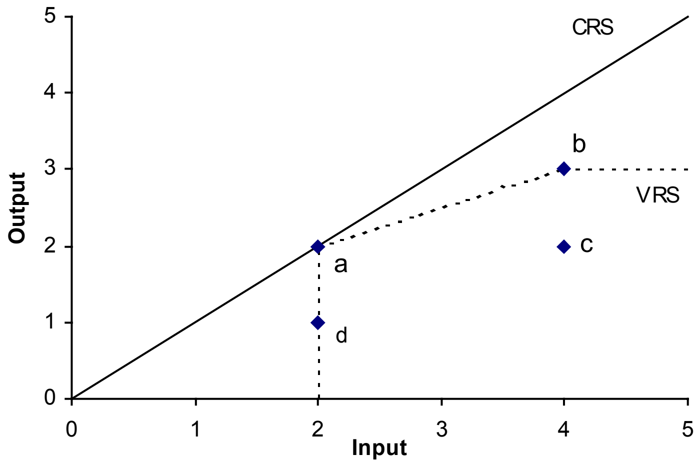

Figure 1. The DEA model.

The frontier envelops the data more or less tightly, depending on the assumed scale properties. If constant returns to scale (CRS) are assumed, the frontier is a straight line. If variable returns to scale (VRS) are imposed, the frontier becomes piece-wise linear as shown by the dashed line. Technical efficiency is either defined in the output- or in the input-direction. Output-orientated technical efficiency is, analogous to the SFA, the ratio of observed to potential output given inputs. Input-orientated technical efficiency is the ratio of the minimum amount of input required to produce the observed output, to observed inputs. The two measures differ under VRS but are the same under CRS.[1] Both measures are bounded between one and zero.[2]

[1] In figure 1, CRS-efficiency for firm *c* is ½ in both the output- and input-direction. The VRS-efficiencies are 2/3 in the output- and ½ in the input-direction.

There are three major specification issues to consider when specifying a DEA-model. These includes the choice of scale properties of the technology, whether to use an input or output-based efficiency measure, and the choice of reference set to identify the frontier. With respect to the scale and efficiency specifications, I choose a VRS-frontier and measure efficiency in the output-direction. In principle, these specifications are identical to the ones adopted in the SFA-model in LB. The choice of reference technology has two dimensions: the level of aggregation of firms and the behaviour of the frontier over time. I assume a single intertemporal frontier, motivated by the unbalancedness of the panel: assessments of more than one reference technology might otherwise result in dramatic and unrealistic frontier shifts over time due to the entry or exit of best-practise firms. Separate sector and pooled models are evaluated.

With these specifications the linear programming problem for observation s ($s = 1,\ldots,S$) of a firms in one of the years, producing one output y and K inputs x, is specified as (drawn from Färe and Grosskopf 1996):

$$\frac{1}{TE_s} = Max_{\lambda}\theta \qquad\qquad m = 1,...,S \qquad (5)$$

subject to the following constraints:

$$\theta\, y_s \leq \sum_{m=1}^{S} \lambda_m y_m \qquad (6)$$

$$x_{js} \geq \sum_{m=1}^{S} \lambda_m x_{jm}, \qquad\qquad j = 1,...,K \qquad (7)$$

$$\sum_{m=1}^{S} \lambda_m = 1 \qquad (8)$$

$$\lambda_m \geq 0, \qquad\qquad m = 1,\ldots,S \qquad (9)$$

where TE_s is output-orientated technical efficiency. Constraint (6) ensures that the maximally inflated output of observation s, $\theta\, y_s$, can be produced as a

[2] Coelli (1996) uses these definitions in his software adopted in this paper. Alternative definitions exist, for instance in Färe and Grosskopf (1996), who define an input distance function as the inverse of my definition of input-orientated technical efficiency.

linear combination of the outputs by all other observations given the weights $\lambda_{m.}$. Restriction (7) conditions this linear combination to use no more inputs than observation s. VRS are obtained by restricting the sum of the weights to one in equation (8) which is removed if a CRS frontier is preferred. Finally, (9) restricts the weights to be non-negative.

Second-step analysis of DEA-efficiency scores

As mentioned in the introduction, the second-stage approach is not by any means unproblematic.[3] First, there is the issue of how one separates the variables as either inputs or determinants for efficiency. Theory does not guide us here, and the distinction must be made on a case-by-case basis. Secondly, inputs and determinants may be correlated and so cause biased and inconsistent estimates in either step. This is an obvious critique against a two-stage SFA, but whether the same argument applies to a two-step DEA is not as obvious. One could perhaps argue that DEA-efficiency is a type of index and therefore remains unaffected by such correlation. Finally, the distribution of efficiencies is confined to the (0,1]-interval with a mass point at one corresponding to the population of frontier firms. Thus, using efficiency as the dependent variable in a regression model may cause problems.

In the seven applications of the two-stage DEA model available to me, neither of the first two points are seriously addressed. Some attention is directed to the latter and different regression models are proposed for the second-step analysis. These include OLS (Nyman and Bricker, 1989), Tobit (Bjurek, Kjulin and Gustafsson, 1992; McCarthy and Yaisawarng, 1993, Kooreman, 1994; Zheng, Liu and Bigsten, 1998) and the logistic regression model (Ray, 1988; Brännlund, Färe and Grosskopf, 1996). In the Tobit-studies, the choice of model is motivated on the idea that efficiency can be regarded as censored, which implies that there exists a latent variable that can take values greater than

[3] See Knox Lovell (1993, p 53f), Grosskopf (1993, p 165) and the workshop discussion in Journal of Productivity Analysis 7 (1996, p 343-345).

one.[4] Clearly, the existence of such a latent variable is inconsistent with the definition of the frontier. Nevertheless, from a purely statistical point of view, the Tobit model could be an appropriate stochastic specification for this particular purpose.

A functional form that precludes the existence of nonsense predicted values for technical efficiency is the logistic model with an additive error term, proposed by Ray (1988),

$$TE_{it} = \frac{1}{1+\exp(Z_{it}\delta)} + \eta_{it}, \tag{10}$$

---

[4] Some citations from these studies are illustrative:
"As the dependent variable is restricted to values between zero and one, and a considerable number of observations have zero value for the dependent variable, a Tobit model was adopted for estimation." (Bjurek, Kjulin and Gustafsson, 1992, p 185).

"Since efficiency scores computed from the DEA model are truncated from below at one, an OLS regression would produce biased and inconsistent estimates. --- …the Tobit model is appropriate when it is possible for the dependent variable to have values beyond the truncation point, yet those values are not observable. *This is likely to be the case for the DEA efficiency scores* [my emphasis]. Given our sample, the best observable DMUs receive scores of one. We would argue that it is likely that some DMUs might perform better than the best DMUs in our sample. If these unobservable DMUs could be compared with a reference frontier constructed from the observable DMUs included in our sample, they would have efficiency scores, TE^*_k less than one." (McCarthy and Yaisawarng, 1993, p 276 and footnote 4, p 277).

"Since by definition there is always a nonnegligible proportion of observations reaching the maximum score of one, censored regression models will be employed. In Nyman and Bricker (1989), a linear regression model was used to explain the score differences. It is well-documented, however, that OLS applied to a censored regression model yields estimates that are asymptotically biased toward zero." (Kooreman, 1994, p 310).

"Due to a relatively large number of fully efficient DEA estimates, the distribution of efficiency is truncated from above at unity. Applying the OLS method would produce biased parameter estimates. One way to get around this problem is to employ a limited dependent-variable model; we chose a censored regression model… [Tobit] --- The Tobit model gives the parameter estimates of *the original normal distribution of technical efficiency* [my emphasis] while taking account of the censored distribution of the DEA efficiency scores. We are particularly interested in *the original normal distribution* [my emphasis], because under this distribution the probability of being fully efficient will be the same as it is for its being extremely inefficient."(Zheng, Liu and Bigsten, 1998, p 478-9).

where Z_{it} is a vector of determinants with an associated parameter vector δ, and η is the disturbance term. The specification ensures that *TE* belongs the unit interval for any values of Z_{it} and δ. The additive error term is assumed symmetric, which may be questionable given that it always is restricted to the $\left\{\frac{\exp(Z_{it}\delta)}{1+\exp(Z_{it}\delta)}, -\frac{1}{1+\exp(Z_{it}\delta)}\right\}$-interval. A more sensible formulation of the residual would be the usual logistic regression model, adopted by Brännlund *et al* (1996) for the same purpose,

$$TE_{it} = \frac{1}{1+\exp(Z_{it}\delta+\varepsilon_{it})}, \tag{11}$$

where ε_{it} is the conventional mean-zero normal error term, distributed identically and independently of the exogenous variables. Equation (11) can be linearized according to

$$\ln\left(\frac{1-TE_{it}}{TE_{it}}\right) = Z_{it}\delta+\varepsilon_{it} \tag{12}$$

which is estimable using OLS. For practical considerations, however, the logistic regression models in (8) and (9) cannot be employed when the sample includes fully efficiency firms ($TE = 1$), which indeed always is the case for DEA. In that case, non-linear least squares estimation of (10) remains the only choice unless one is willing to scale *TE* somewhat in order to avoid it taking border values.

The marginal effects of the logistic models in (10) and (11) are:

$$\frac{\partial TE}{\partial Z} = -\delta(1-TE_{it})TE_{it}.$$

The approach taken here is to use OLS, Tobit and the two logistic models, defined by (10) and (11) above. For the linearised version of the logistic model in (12), two scaling factors are used: .9 and .99. The motivation for using all models outlined above is to see whether they qualitatively differ. The explanatory variables in Z_{it} includes measures of firm size and age, defined as the log of intermediate inputs and log years of age, respectively. These variables are included in levels, squared and interacted with each other.

In all second stage models, the marginal effects are defined as the partial derivative of the *level* of technical efficiency with respect to log age and size. Hence, they are interpreted as the *unit*-change in efficiency from a percentage change in age or size.

3. Data

The data consist of an unbalanced panel of Kenyan manufacturing firms in the food, wood, textile and metal sectors, observed during 1992-1994. It is drawn from the World Bank Regional Program on Enterprise Development (RPED) surveys and has a total of 656 observations on 275 urban firms. The four sectors covered in this study represent approximately 72% of total manufacturing in Kenya (Department of Economics 1995).

The definitions of output and inputs are as follows. Output is the value of all output produced by the firm during the year. Operating capital is defined as the replacement value of the machinery and equipment corrected for capacity utilisation. Wages is the total wage bill including all allowances. Intermediate inputs include costs for raw materials, solid and liquid fuel, electricity and water. All output and inputs are converted to 1992 Kenyan shillings using appropriate deflators. Observations with missing values of output or age were deleted, while missing values of inputs were imputed, leaving a sample of 563 observations on 235 firms available for estimation. Descriptive statistics of these data are presented in table 1.

A general feature of the data is that the distributions of the variables are strongly skewed to the left: a few very large firms coexist with a sizeable number of small and medium-sized firms. Firms in the food sector are generally larger, whereas firm age differ little across sectors. Several sources of sample noise exist, including intentional misinformation by the firms, inaccuracy in the measurement of flow variables, and imprecise price deflators of outputs and inputs over time.

Table 1. Descriptive statistics of the data used.

Variable	Obs	Mean	Std Dev	Min	Max
Output	563	41,688	108,534	5	1,150,000
Capital	563	30,884	128,947	0	1,923,077
Wages	563	3,314	8,141	1	94,300
Intermediate inputs	563	26,089	72,611	2	920,647
Firm age	563	19.50	14	2	74

4. Results

First step: Technical efficiencies

Estimated technical efficiencies are presented in table 2 below. Several findings are noteworthy. Firstly, mean efficiencies are systematically lower for DEA in all firm categories but one. Inefficiency levels (1 - *TE*) for SFA are about half of those captured by the DEA-measure. So, half of the variation in output that in DEA is interpreted as inefficiency is regarded as statistical noise in SFA.

Secondly, in contrast to SFA, DEA-efficiencies are higher for the sector models than for the pooled model, indicating a negative relationship between sample size and technical efficiency. Indeed, the existence of such a relationship has been established in a recent study based on Monte Carlo simulations (Zhang and Bartels, 1995).

Thirdly, mean efficiency increases with every larger size category with few exceptions. These exceptions include the smallest size categories in the food, wood and the pooled models, and also the two smallest groups in metals. Finally, the correlation coefficients between the DEA-VRS- and SFA-efficiencies are higher than the corresponding ones between DEA-CRS and SFA. This leads one to believe that the VRS-frontier is a more sensible specification of the DEA-model than the CRS-frontier.

Table 2. Mean estimated technical efficiencies of Kenyan manufacturing firms using DEA-VRS and SFA (reported in LB) in pooled and sector models.

	Sector models				Pooled model
DEA-VRS	Food	Wood	Textiles	Metals	
Very small	0.63	0.52	0.44	0.46	0.34
Small	0.33	0.42	0.49	0.48	0.31
Medium	0.46	0.46	0.56	0.42	0.35
Large	0.52	0.59	0.61	0.43	0.39
Very large	0.62	0.82	0.74	0.72	0.54
All	0.53	0.52	0.54	0.50	0.38
Standard deviation	0.26	0.27	0.27	0.26	0.22
Efficient firms (TE=1)	16	22	21	13	26
SFA					
Very small	0.68	0.42	0.56	0.76	0.68
Small	0.67	0.53	0.71	0.80	0.72
Medium	0.78	0.77	0.83	0.77	0.79
Large	0.76	0.88	0.90	0.80	0.81
Very large	0.81	0.93	0.91	0.87	0.84
All	0.77	0.68	0.76	0.80	0.77
Standard deviation	0.15	0.24	0.20	0.12	0.14
Correlation coefficients between various technical efficiency estimates					
ρ (DEA-VRS, SFA)	0.52	0.39	0.59	0.57	0.61
ρ (DEA-CRS, SFA)	0.53	0.16	0.34	0.47	0.55
ρ (DEA-VRS, DEA-CRS)	0.88	0.80	0.79	0.82	0.89
Observations	125	157	137	144	563

NOTE: The size categories are based on intermediate inputs, M, measured in millions of Kenyan 1992 shillings: Very small: M<.15; Small: .15<M<1; Medium: 1<M<5; Large: 5<M<30: very large: M>30.

Cross-plots of efficiency scores obtained using the two approaches are displayed in Figures 2 and 3 below. The SFA-estimates are higher for those observations that lay above a 45-degree line, which is true for most observations. The match is worse in the sector models compared to the pooled model. Notably, a small number of observations are efficient in the DEA-model but very inefficient according to the SFA-model.

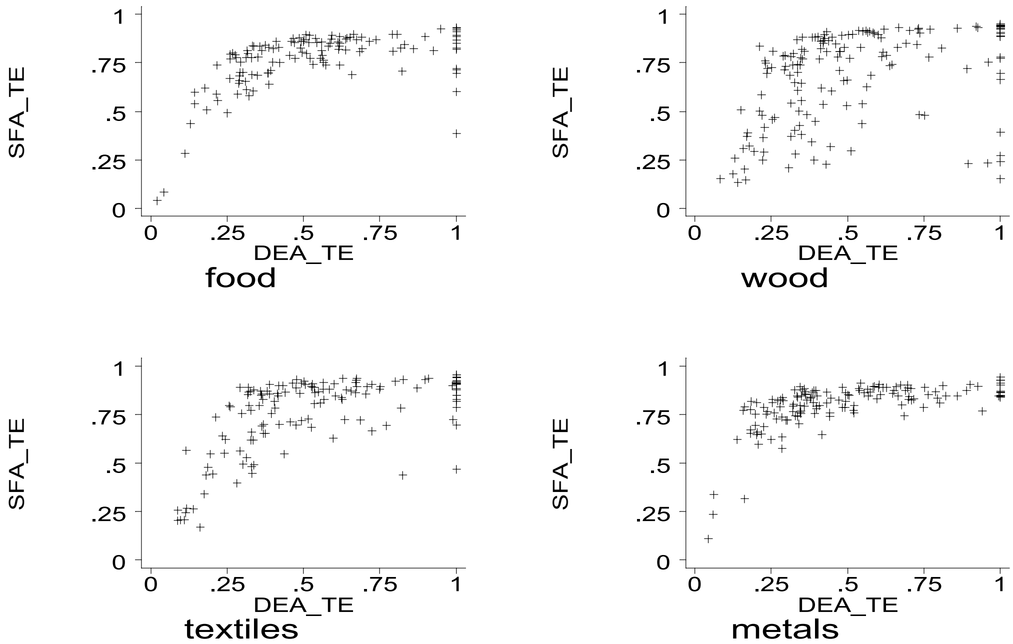

Figure 2. Cross plots of technical efficiencies in the SFA and DEA sector models.

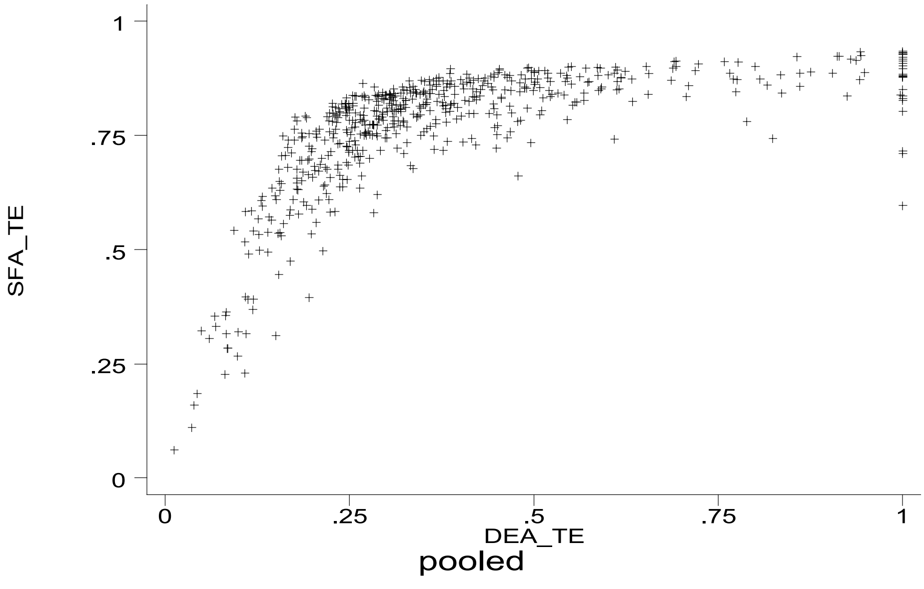

Figure 3. Cross plots of technical efficiencies in SFA and DEA-VRS models.
Pooled model.

These inconsistencies may be caused by observations for which one or more of the constraints in the linear programming problems are slack.[5] Such problems may not only occur along the edges of the constructed frontier hyperplanes, but also in the middle of the sample. Closer investigation of these observations is not conducted here.

Second-step analysis of DEA-efficiencies

Results from the second-stage models are presented in tables A1-A5. Pooled and sector models were estimated, using as dependent variable the DEA-efficiency scores obtained from pooled and sector frontiers. The fit in terms of R-square (except for the Tobit models) hovers around .2, which is in the range of the studies referred to above.

Joint tests of the estimated parameters for the age and size effects were conducted using a series of Wald tests, reported at the bottom of the tables A1 – A5. All pooled and sector models reject the null of no size effects, a finding somewhat at variance with LB where size only was significant in the pooled, wood and textile models. Firm age is insignificant everywhere except in textiles, where the variable is significant in all estimations (except in the non-linear logistic equation, table A5). This result is the same as in LB.

The marginal effects on technical efficiency with respect to age and size are reported by sector in table 3 and by sector and size in tables A6 and A7. The age-effects display quite a large variation across models. However, as noted above they are all insignificant except in textiles, where, surprisingly, SFA predicts a negative relationship and DEA a positive (table 3). Closer investigation (table A6) removes most of this contradiction: age has a negative effect for small and medium-sized firms and positive for larger ones in both SFA and DEA.

[5] Firm *d* in Figure 1 is VRS-efficient (but not CRS-efficient) despite the fact that it can expand output by 100%. Thus, the output constraint in (6) is slack.

Table 3. Mean marginal effects of age and size on technical efficiency. Evaluated for the SFA-model in the LB study, and for each of the models presented in the tables A1-A5.

Age effects	SFA	OLS	Tobit-L[a]	Tobit-O[b]	log-9[c]	log-99[d]	log-nlin[e]
Food	0.061	-0.009	-0.010	-0.010	0.000	-0.012	-0.009
Wood	0.032	-0.025	-0.034	-0.032	-0.023	-0.033	-0.029
Textile	-0.048	0.036	0.030	0.028	0.035	0.056	0.034
Metal	-0.094	-0.073	-0.012	-0.010	-0.073	-0.052	-0.077
Pooled	0.020	-0.008	-0.008	-0.008	-0.006	-0.008	-0.010
Size-effects							
Food	0.012	0.044	0.056	0.055	0.042	0.042	0.043
Wood	0.083	0.031	0.012	0.012	0.029	0.025	0.029
Textile	0.058	0.039	0.011	0.010	0.040	0.037	0.0374
Metal	0.020	0.021	0.031	0.030	0.017	0.003	0.019
Pooled	0.020	0.024	0.024	0.024	0.026	0.027	0.023

a) Marginal effects for the latent (unobserved) variable in the Tobit model.
b) Marginal effects for the observed variable in the Tobit model
c) Marginal effects based on the linearised logistic model in (12) estimated using OLS where technical efficiency was scaled by 0.9.
d) Marginal effects based on the linearised logistic model in (12) estimated using OLS where technical efficiency was scaled by 0.99.
e) Marginal effects based on the logistic model estimated using non-linear least squares.

More can be said about the size effects given its strongly significant parameters according to the Wald tests. All mean values, and most category-means, are positive, revealing a positive size-efficiency relationship for most establishments. A doubling of firm size is predicted to be associated with an increase of technical efficiency by 012 - .083 units according to the SFA-model, and by .011 - .053 units in the DEA second-stage models. A general difference between SFA and DEA is how the magnitude of the relationship changes with firm size. While it *de*creases in SFA, it *in*creases in DEA. Probably, the inconsistency is an outcome of different scale properties of the SFA and DEA frontiers, implying slightly higher returns in most regions in the former.

Correlation coefficients of the marginal effects are reported for the pooled models in table 4 below, and for the sector models in tables A8 and A9. These reveal considerable heterogeneity across SFA and DEA, but less so between different second-step DEA models. Also pooling appears to play a role.

The age effects among the SFA- and DEA-models are positively correlated in almost all cases (the exception is food, table A6), indicating that both approaches yield similar predictions for this variable.

Quite shockingly, the size-effects of SFA and DEA are negatively correlated in all models except metals, suggesting considerable divergences in the estimated size-effects. This is probably due to the fact that the size-efficiency association becomes stronger for larger firms in DEA, whereas it goes the other way around in SFA. Nevertheless, the overall means are basically the same.

Table 4. Correlation coefficients and means of marginal effects of technical efficiency with respect to firm age and size for pooled models.

Age-effects	SFA	OLS	Tobit-L[a]	Tobit-O[b]	log-9[c]	log-99[d]	log-nlin[e]
SFA	1						
OLS	0.803	1					
Tobit-L	0.808	0.998	1				
Tobit-O	0.809	0.997	0.999	1			
log-9	0.805	0.989	0.993	0.996	1		
log-99	0.818	0.977	0.985	0.988	0.993	1	
log-nlin	0.799	0.994	0.988	0.990	0.986	0.968	1

Size-effects	SFA	OLS	Tobit-L[a]	Tobit-O[b]	log-9[c]	log-99[d]	log-nlin[e]
SFA	1						
OLS	-0.084	1					
Tobit-L	-0.084	1.000	1				
Tobit-O	-0.087	1.000	1.000	1			
log-9	-0.070	0.996	0.996	0.997	1		
log-99	-0.064	0.988	0.988	0.987	0.990	1	
log-nlin	-0.086	0.997	0.997	0.997	0.998	0.995	1

a) – e) See Table 3.

6. Conclusion

The comparison conducted in this paper suggests that the basic conclusions regarding the association between technical efficiency and age-size are the same irrespective of whether a SFA or two-step-DEA approach is adopted. Larger firms *are* more efficient, and this is true when the effects of subsector, period of observation and firm age are controlled for. Also, firm age has no systematic influence on technical efficiency except in textiles, where it is negative for small and positive for large firms.

Nevertheless, the results from the two approaches differ in at least two respects. One is the level of the estimated technical efficiencies, which ranges between 0.38 and 0.54 in DEA and between 0.68 and 0.80 in SFA, suggesting that about half of the variation in output that in DEA is regarded as variation in efficiency, is attributed to statistical noise in SFA. The second difference is how the size-efficiency relationship varies with the absolute size of the establishment. Whereas it becomes stronger with size according to the DEA-second step models, it becomes weaker in the SFA-model. Consequently, the size-effects predicted by the two approaches are negatively correlated. Serious as this may seem, both approaches still report positive relationships. I therefore conclude that the marginal effects are consistent between the two approaches in terms of overall significance levels and directions, but not in terms of magnitudes.

Another issue concerns the correct estimation procedure in the DEA-second-stage model. The evidence presented suggests the issue to be of limited importance: the main conclusions hold irrespective of which model you chose.

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Appendix

Table A1. OLS regression results. Dependent variable: DEA-VRS technical efficiency. White-corrected robust standard errors are presented in parentheses immediately under the parameter coefficients, rounded to two digits. The parameter coefficients are rounded to the same number of decimals.

Variable	Pooled	Food	Wood	Textile	Metal
Constant	2.17 (0.34)	2.87 (0.83)	2.93 (0.69)	2.68 (0.58)	3.36 (0.75)
age	-0.020 (0.085)	-0.24 (0.21)	0.26 (0.21)	-0.29 (0.16)	0.28 (0.20)
age^2	-0.017 (0.014)	0.018 (0.038)	-0.014 (0.031)	-0.025 (0.027)	-0.094 (0.065)
size	-0.262 (0.045)	-0.30 (0.11)	-0.430 (0.094)	-0.293 (0.089)	-0.46 (0.11)
$size^2$	0.0091 (0.0016)	0.0101 (0.0032)	0.0178 (0.0032)	0.0086 (0.0035)	0.0156 (0.0039)
$age \times size$	0.0072 (0.0059)	0.008 (0.012)	-0.0145 (0.0096)	0.033 (0.012)	0.010 (0.023)
Year 1993	-0.031 (0.021)	-0.031 (0.053)	0.036 (0.051)	-0.106 (0.052)	-0.062 (0.047)
Year 1994	-0.024 (0.021)	0.037 (0.052)	-0.036 (0.043)	-0.110 (0.050)	-0.033 (0.048)
Wood	-0.033 (0.028)				
Textiles	-0.058 (0.027)				
Metal	-0.073 (0.027)				

Wald hyptheses tests (Probability of the null)					
H_0: $age=age^2=size=size^2=age \times size=0$	0.000	0.000	0.000	0.000	0.000
H_0: $age = age^2 = age \times size = 0$	0.450	0.670	0.087	0.013	0.152
H_0: $size = size^2 = age \times size = 0$	0.000	0.000	0.000	0.000	0.000
R-square	0.198	0.200	0.221	0.238	0.217
Observations	563	125	157	137	144

NOTE: Size is the natural logarithm of intermediate inputs employed by the firm. Firm age is also measures in natural logarithms.

Table A2. Tobit model results. Dependent variable: DEA-VRS technical efficiency. Standard errors are given in parentheses immediately under the parameter coefficients, rounded to two digits. The parameter coefficients are rounded to the same number of decimals.

Variable	Pooled	Food	Wood	Textile	Metal
Constant	2.32 (0.28)	2.26 (0.79)	1.45 (0.62)	3.65 (0.55)	1.37 (0.55)
age	-0.029 (0.081)	-0.06 (0.19)	0.16 (0.19)	-0.25 (0.14)	-0.11 (0.18)
age^2	-0.017 (0.015)	0.010 (0.036)	-0.023 (0.033)	-0.022 (0.023)	-0.033 (0.053)
size	-0.282 (0.037)	-0.27 (0.11)	-0.195 (0.084)	-0.445 (0.072)	-0.150 (0.076)
$size^2$	0.0097 (0.0013)	0.0103 (0.0038)	0.0078 (0.0030)	0.0135 (0.0025)	0.0045 (0.0030)
$age \times size$	0.0077 (0.0058)	-0.000 (0.013)	-0.004 (0.011)	0.029 (0.010)	0.019 (0.019)
Year 1993	-0.030 (0.021)	-0.050 (0.051)	0.038 (0.041)	-0.063 (0.040)	-0.046 (0.038)
Year 1994	-0.024 (0.022)	0.012 (0.053)	-0.014 (0.040)	-0.0639 (0.041)	-0.020 (0.039)
Wood	-0.033 (0.027)				
Textiles	-0.058 (0.027)				
Metal	-0.073 (0.027)				
Sigma	0.2093 (0.0065)	0.235 (0.016)	0.208 (0.012)	0.196 (0.012)	0.187 (0.011)
Wald hyptheses tests (Probability of the null)					
H_0: $age=age^2=size=size^2=age\times size=0$	0.000	0.000	0.077	0.000	0.000
H_0: $age = age^2 = age\times size = 0$	0.473	0.972	0.509	0.047	0.733
H_0: $size = size^2 = age\times size = 0$	0.000	0.000	0.024	0.000	0.000
Observations	563	125	157	137	144

NOTE: See table A1.

Table A3. OLS regression results of linearized logistic models. Dependent variable: DEA-VRS technical efficiency scaled by the factor .9. White-corrected robust standard errors are presented in parentheses immediately under the parameter coefficients, rounded to two digits. The parameter coefficients are rounded to the same number of decimals.

Variable	Pooled	Food	Wood	Textile	Metal
Constant	-7.0	-10.8	-10.9	-10.1	-12.9
	(1.6)	(4.0)	(3.3)	(2.7)	(3.5)
age	0.17	1.0	-1.19	1.49	-1.26
	(0.42)	(1.0)	(0.96)	(0.75)	(0.91)
age^2	0.091	-0.05	0.06	0.12	0.46
	(0.067)	(0.18)	(0.14)	(0.12)	(0.30)
size	1.12	1.41	1.96	1.36	2.09
	(0.22)	(0.49)	(0.44)	(0.42)	(0.49)
$size^2$	-0.0380	-0.046	-0.081	-0.039	-0.069
	(0.0075)	(0.015)	(0.015)	(0.016)	(0.018)
$age \times size$	-0.043	-0.044	0.068	-0.166	-0.06
	(0.029)	(0.062)	(0.044)	(0.053)	(0.11)
Year 1993	0.178	0.20	-0.15	0.49	0.32
	(0.099)	(0.26)	(0.23)	(0.24)	(0.22)
Year 1994	0.121	-0.12	0.16	0.51	0.14
	(0.094)	(0.23)	(0.20)	(0.23)	(0.22)
Wood	0.11				
	(0.13)				
Textiles	0.22				
	(0.13)				
Metal	0.29				
	(0.12)				

Wald hyptheses tests (Probability of the null)					
H_0: $age=age^2=size=size^2=age\times size=0$	0.000	0.000	0.000	0.000	0.000
H_0: $age = age^2 = age\times size = 0$	0.338	0.799	0.099	0.004	0.200
H_0: $size = size^2 = age\times size = 0$	0.000	0.000	0.000	0.000	0.000
R-square	0.182	0.166	0.220	0.243	0.208
Observations	563	125	157	137	144

NOTE: See table A1.

Table A4. OLS regression results of linearized logistic models. Dependent variable: DEA-VRS technical efficiency scaled by the factor .99. White-corrected robust standard errors are presented in parentheses immediately under the parameter coefficients, rounded to two digits. The parameter coefficients are rounded to the same number of decimals.

Variable	Pooled	Food	Wood	Textile	Metal
Constant	**-11.2**	**-19.4**	**-20.7**	**-19.3**	**-20.4**
	(2.7)	**(6.4)**	**(5.3)**	**(4.4)**	**(5.6)**
age	**0.30**	**1.5**	**-1.8**	**2.1**	**-1.8**
	(0.64)	**(1.6)**	**(1.5)**	**(1.2)**	**(1.5)**
age^2	**0.107**	**-0.058**	**0.07**	**0.21**	**0.62**
	(0.096)	**(0.28)**	**(0.21)**	**(0.17)**	**(0.44)**
size	**1.6526**	**2.36**	**3.44**	**2.59**	**3.16**
	(0.35)	**(0.79)**	**(0.72)**	**(0.67)**	**(0.79)**
size^2	**-0.055**	**-0.074**	**-0.139**	**-0.076**	**-0.102**
	(0.012)	**(0.025)**	**(0.024)**	**(0.026)**	**(0.029)**
age×size	**-0.058**	**-0.07**	**0.107**	**-0.252**	**-0.08**
	(0.044)	**(0.10)**	**(0.073)**	**(0.082)**	**(0.16)**
Year 1993	**0.17**	**0.14**	**-0.21**	**0.69**	**0.44**
	(0.14)	**(0.40)**	**(0.36)**	**(0.38)**	**(0.32)**
Year 1994	**0.13**	**-0.18**	**0.29**	**0.74**	**0.21**
	(0.13)	**(0.38)**	**(0.32)**	**(0.37)**	**(0.34)**
Wood	**0.17**				
	(0.18)				
Textiles	**0.28**				
	(0.18)				
Metal	**0.36**				
	(0.18)				

Wald hyptheses tests (Probability of the null)					
H_0: $age=age^2=size=size^2=age\times size=0$	**0.000**	**0.008**	**0.000**	**0.000**	**0.000**
H_0: $age = age^2 = age\times size = 0$	**0.424**	**0.767**	**0.214**	**0.001**	**0.426**
H_0: $size = size^2 = age\times size = 0$	**0.000**	**0.002**	**0.000**	**0.000**	**0.000**
R-square	**0.155**	**0.139**	**0.224**	**0.227**	**0.178**
Observations	**563**	**125**	**157**	**137**	**144**

NOTE: See table A1.

Table A5. Nonlinear least squares regression results of linearized logistic models. Dependent variable: DEA-VRS technical efficiency. Approx. Std Err 's are presented in parentheses immediately under the parameter coefficients, rounded to two digits. The parameter coefficients are rounded to the same number of decimals.

Variable	Pooled	Food	Wood	Textile	Metal
Constant	-7.10 (1.16)	-10.0 (3.8)	-10.1 (3.77)	-10.1 (3.8)	-11.6 (3.0)
age	0.05 (0.34)	0.97 (0.83)	-1.3 (1.1)	1.31 (0.84)	-1.31 (0.99)
age^2	0.084 (0.066)	-0.07 (0.15)	0.04 (0.18)	0.11 (0.12)	0.38 (0.28)
size	1.11 (0.16)	1.29 (0.53)	1.85 (0.50)	1.36 (0.49)	1.91 (0.42)
size^2	-0.0385 (0.0056)	-0.043 (0.018)	-0.079 (0.019)	-0.040 (0.016)	-0.066 (0.017)
age×*size*	-0.031 (0.024)	-0.035 (0.057)	0.087 (0.079)	-0.148 (0.062)	-0.03 (0.10)
Year 1993	0.137 (0.091)	0.16 (0.22)	-0.15 (0.20)	0.45 (0.22)	0.25 (0.20)
Year 1994	0.104 (0.092)	-0.15 (0.23)	0.156 (0.020)	0.47 (0.22)	0.14 (0.20)
Wood	0.14 (0.11)				
Textiles	0.25 (0.11)				
Metal	0.32 (0.11)				

Wald hyptheses tests (Probability of the null)					
H_0: $age=age^2=size=size^2=age\times size=0$	0.000	0.001	0.000	0.001	0.000
H_0: $age = age^2 = age\times size = 0$	0.448	0.663	0.555	0.096	0.198
H_0: $size = size^2 = age\times size = 0$	0.000	0.000	0.000	0.000	0.000
R-square	0.198	0.199	0.218	0.234	0.216
Observations	563	125	157	137	144

NOTE: See table A1.

Table A6. Mean marginal effects on technical efficiency of firm age. Evaluated for the SFA-model in the LB study, and for each of the models presented in tables A1 – A5.

Pooled	SFA	OLS	Tobit-L[a]	Tobit-O[b]	log-9[c]	log-99[d]	log-nlin[e]
Very small	-0.036	-0.024	-0.026	-0.025	-0.028	-0.042	-0.025
Small	0.027	-0.010	-0.011	-0.010	-0.009	-0.014	-0.009
Medium	0.021	-0.017	-0.017	-0.016	-0.016	-0.020	-0.019
Large	0.041	0.001	0.001	0.001	0.005	0.008	-0.002
Very large	0.044	0.008	0.010	0.010	0.017	0.024	0.005
ALL	0.020	-0.008	-0.008	-0.008	-0.006	-0.008	-0.010
Food							
Very small	0.016	-0.076	-0.022	-0.022	-0.064	-0.063	-0.066
Small	0.076	-0.059	-0.023	-0.022	-0.045	-0.079	-0.057
Medium	0.043	-0.023	-0.010	-0.010	-0.016	-0.040	-0.023
Large	0.063	-0.006	-0.009	-0.009	0.004	-0.007	-0.006
Very large	0.071	0.024	-0.003	-0.003	0.033	0.030	0.021
ALL	0.061	-0.009	-0.010	-0.010	0.000	-0.012	-0.009
Wood							
Very small	0.099	0.020	-0.018	-0.017	0.024	0.030	0.031
Small	0.056	0.002	-0.013	-0.011	0.004	0.000	0.000
Medium	0.000	-0.039	-0.046	-0.043	-0.040	-0.065	-0.049
Large	-0.007	-0.057	-0.043	-0.042	-0.061	-0.084	-0.076
Very large	-0.008	-0.100	-0.074	-0.073	-0.074	-0.051	-0.083
ALL	0.032	-0.025	-0.034	-0.032	-0.023	-0.033	-0.029
Textile							
Very small	-0.128	-0.047	-0.042	-0.041	-0.058	-0.063	-0.049
Small	-0.068	-0.004	-0.006	-0.005	-0.010	0.005	-0.003
Medium	-0.030	0.026	0.020	0.019	0.028	0.058	0.031
Large	0.014	0.103	0.088	0.083	0.118	0.170	0.109
Very large	0.024	0.179	0.154	0.151	0.168	0.180	0.145
ALL	-0.048	0.036	0.030	0.028	0.035	0.056	0.034
Metal							
Very small	-0.071	-0.048	-0.056	-0.050	-0.056	-0.032	-0.045
Small	-0.054	-0.015	-0.017	-0.016	-0.012	0.024	-0.017
Medium	-0.146	-0.115	-0.025	-0.023	-0.111	-0.118	-0.117
Large	-0.113	-0.099	0.005	0.005	-0.102	-0.094	-0.114
Very large	-0.106	-0.115	0.031	0.031	-0.108	-0.071	-0.118
ALL	-0.094	-0.073	-0.012	-0.010	-0.073	-0.052	-0.077

a) Marginal effects for the latent (unobserved) variable in the Tobit model
b) Marginal effects for the observed variable in the Tobit model.
c) Marginal effects based on the linearised logistic model in (12) estimated using OLS where technical efficiency was scaled by .9.
d) Marginal effects based on the linearised logistic model in (12) estimated using OLS where technical efficiency was scaled by .99.
e) Marginal effects based on the logistic model estimated using non-linear least squares.

Table A7. Mean marginal effects on technical efficiency of firm size. Evaluated for the SFA-model in the LB study, and for each of the models presented in tables A1 – A5.

Pooled	SFA	OLS	Tobit-L[a]	Tobit-O[b]	log-9[c]	log-99[d]	log-nlin[e]
Very small	0.024	-0.045	-0.049	-0.047	-0.038	-0.069	-0.044
Small	0.020	-0.008	-0.010	-0.010	-0.005	-0.017	-0.008
Medium	0.024	0.025	0.026	0.024	0.024	0.028	0.023
Large	0.018	0.054	0.056	0.054	0.053	0.072	0.053
Very large	0.014	0.093	0.099	0.098	0.098	0.120	0.093
ALL	0.020	0.024	0.024	0.024	0.026	0.027	0.023
Food							
Very small	0.016	-0.063	-0.047	-0.046	-0.070	-0.079	-0.058
Small	0.010	-0.016	0.000	0.000	-0.025	-0.061	-0.017
Medium	0.017	0.014	0.025	0.023	0.009	-0.007	0.014
Large	0.013	0.050	0.061	0.060	0.050	0.060	0.053
Very large	0.008	0.096	0.104	0.104	0.095	0.109	0.089
ALL	0.012	0.044	0.056	0.055	0.042	0.042	0.043
Wood							
Very small	0.096	-0.075	-0.034	-0.033	-0.081	-0.134	-0.078
Small	0.131	-0.007	-0.005	-0.005	-0.008	-0.030	-0.005
Medium	0.081	0.046	0.019	0.018	0.049	0.072	0.050
Large	0.044	0.108	0.046	0.045	0.117	0.156	0.113
Very large	0.018	0.174	0.076	0.075	0.124	0.088	0.111
ALL	0.083	0.031	0.012	0.012	0.029	0.025	0.029
Textile							
Very small	0.078	-0.030	-0.087	-0.084	-0.031	-0.078	-0.034
Small	0.095	0.029	-0.009	-0.009	0.032	0.033	0.030
Medium	0.057	0.067	0.042	0.039	0.078	0.106	0.073
Large	0.026	0.078	0.071	0.067	0.084	0.108	0.080
Very large	0.017	0.105	0.117	0.116	0.083	0.084	0.079
ALL	0.058	0.039	0.011	0.010	0.040	0.037	0.037
Metal							
Very small	0.005	-0.091	-0.007	-0.006	-0.102	-0.147	-0.091
Small	0.017	-0.036	0.008	0.007	-0.041	-0.081	-0.034
Medium	0.025	0.028	0.037	0.034	0.026	0.022	0.029
Large	0.026	0.076	0.050	0.049	0.080	0.100	0.080
Very large	0.026	0.145	0.073	0.073	0.140	0.144	0.127
ALL	0.020	0.021	0.031	0.030	0.017	0.003	0.019

a) – e) See Table A6.

Table A8. Correlation coefficients of marginal age effects in sector models.

Food	SFA	OLS	Tobit-L[a]	Tobit-O[b]	log-9[c]	log-99[d]	log-nlin[e]
SFA	1						
OLS	-0.308	1					
Tobit-L	-0.534	0.896	1				
Tobit-O	-0.533	0.893	1.000	1			
log-9	-0.190	0.979	0.797	0.793	1		
log-99	-0.131	0.887	0.679	0.670	0.940	1	
log-nlin	-0.303	0.996	0.891	0.887	0.983	0.915	1

Wood	SFA	OLS	Tobit-L[a]	Tobit-O[b]	log-9[c]	log-99[d]	log-nlin[e]
SFA	1						
OLS	0.815	1					
Tobit-L	0.607	0.843	1				
Tobit-O	0.609	0.853	0.999	1			
log-9	0.852	0.972	0.812	0.820	1		
log-99	0.860	0.861	0.727	0.727	0.947	1	
log-nlin	0.868	0.949	0.717	0.727	0.988	0.947	1

Textile	SFA	OLS	Tobit-L[a]	Tobit-O[b]	log-9[c]	log-99[d]	log-nlin[e]
SFA	1						
OLS	0.740	1					
Tobit-L	0.742	1.000	1				
Tobit-O	0.734	0.999	0.999	1			
log-9	0.751	0.978	0.978	0.973	1		
log-99	0.772	0.906	0.908	0.894	0.962	1	
log-nlin	0.765	0.971	0.972	0.965	0.998	0.975	1

Metal	SFA	OLS	Tobit-L[a]	Tobit-O[b]	log-9[c]	log-99[d]	log-nlin[e]
SFA	1						
OLS	0.801	1					
Tobit-L	0.479	0.542	1				
Tobit-O	0.475	0.537	0.999	1			
log-9	0.782	0.992	0.584	0.579	1		
log-99	0.777	0.973	0.629	0.624	0.985	1	
log-nlin	0.789	0.992	0.499	0.494	0.993	0.979	1

a) – e) See Table A6.

Table A9. Correlation coefficients of marginal size effects in sector models.

Food	SFA	OLS	Tobit-L[a]	Tobit-O[b]	log-9[c]	log-99[d]	log-nlin[e]
SFA	1						
OLS	-0.022	1					
Tobit-L	-0.113	0.993	1				
Tobit-O	-0.116	0.993	1.000	1			
log-9	-0.002	0.991	0.980	0.979	1		
log-99	-0.057	0.936	0.928	0.926	0.966	1	
log-nlin	-0.010	0.984	0.974	0.972	0.998	0.972	1

Wood	SFA	OLS	Tobit-L[a]	Tobit-O[b]	log-9[c]	log-99[d]	log-nlin[e]
SFA	1						
OLS	-0.495	1					
Tobit-L	-0.504	0.999	1				
Tobit-O	-0.505	0.999	1.000	1			
log-9	-0.476	0.968	0.967	0.964	1		
log-99	-0.453	0.876	0.875	0.867	0.959	1	
log-nlin	-0.453	0.957	0.955	0.951	0.998	0.968	1

Textile	SFA	OLS	Tobit-L[a]	Tobit-O[b]	log-9[c]	log-99[d]	log-nlin[e]
SFA	1						
OLS	-0.146	1					
Tobit-L	-0.266	0.984	1				
Tobit-O	-0.269	0.982	0.999	1			
log-9	-0.099	0.960	0.930	0.923	1		
log-99	-0.097	0.884	0.863	0.851	0.967	1	
log-nlin	-0.114	0.955	0.932	0.924	0.998	0.978	1

Metal	SFA	OLS	Tobit-L[a]	Tobit-O[b]	log-9[c]	log-99[d]	log-nlin[e]
SFA	1						
OLS	0.523	1					
Tobit-L	0.550	0.967	1				
Tobit-O	0.544	0.971	0.999	1			
log-9	0.526	0.995	0.964	0.967	1		
log-99	0.507	0.969	0.941	0.942	0.984	1	
log-nlin	0.531	0.992	0.953	0.956	0.998	0.988	1

a) – e) See Table A6.

FACTOR INTENSITIES AND SUBSTITUTION IN KENYAN MANUFACTURING[#]

Karl Lundvall*

May 1999

Abstract: Large firms tend to be more capital-intensive than smaller ones in Kenyan manufacturing. Estimated translog production functions suggest this be due to non-homothetic technologies and to different input prices. As output increases from 4 to 50 million Kenyan Shillings, capital intensity increases by 20-160% along an arbitrarily chosen expansion path. The relative marginal products of capital to labour exhibit tendencies to fall with firm size, suggesting a negative relationship between the relative price for capital and firm size. Skilled and unskilled labour exhibit higher substitutability between each other than with capital. Hence, capital may constrain the firm more than skill.

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1. Introduction

A common argument for the promotion of small-scale enterprises in the developing world is the increase in the demand for unskilled labour that is presumed to follow. Such an increase can be warranted in countries with scarce capital and abundant labour because it could represent a shift towards greater allocative efficiency. In addition, it may also reduce unemployment and poverty. This argument rests on a number of assumptions, some of which we will consider at a more detail in this paper with reference to data from Kenyan manufacturing.

First, the argument implicitly assumes that there exists a positive relationship between firm size and capital intensity. Although this is a commonly held view, the evidence is not conclusive. The first purpose of the paper is therefore to investigate whether factor intensities vary systematically with the size of establishments.

Second, given that such a positive relationship exist, it is important to understand its underlying causes. One possibility is that relative factor prices are different, so that small firms face higher input prices for capital relative to labour than do larger ones. The well-documented restricted access to credit for small firms in LDCs together with their ability to circumvent minimum wage legislation supports this assertion. But if this is true, labour demand could be increased if these factor price differences were levelled out, which would be a preferable policy from an allocative efficiency perspective.

Another explanation for capital intensity to rise with firm size is that the technology is not homothetic, which often appear to a maintained, but seldom empirically tested, assumption in the literature. Thus, factor ratios may change with output although the firms continue to equalise technical rate of substitution (TRS) with constant relative factor prices. Pack (1976 and 1982) presents evidence from Kenyan manufacturing and elsewhere suggesting the presence of non-homothetic technologies so that capital intensity *increases* with output under constant TRS. The second objective of the paper is therefore to test for the possible presence and direction of non-homotheticity using translog production functions.

Thirdly, the demand for unskilled labour is also a function of its elasticity of substitution with other factors of production, most notable physical capital and human skill. For instance, if skill is complementary to capital, an increase in skill may result in a reduction of the demand for unskilled labour (Hamermesh 1993, p 383f). These relationships may be important if skill is as scarce, or even more scarce, than capital, which according to Hamermesh generally is the case in many developing economies. To address this, I estimate the substitution elasticities between capital, unskilled and skilled labour using three-factor translog production functions.

The observed relationships between factor intensities and firm size in Kenyan manufacturing and elsewhere are examined in section 2. The theoretical link is discussed in section 3. Section 4 outlines the empirical model and section 5 presents the results. Section 6 concludes.

2. Observed factor intensities

Although it is often presumed that there exists a positive relationship between firm size and capital intensity, the evidence is simply not strong enough to give such a presumption a solid empirical backing. A survey by Little, Mazumdar and Page (1987, p 125f), comprising studies from ten countries and an in-depth case study of India, demonstrates this clearly. For example, in Colombia and Thailand, the smallest size class was not the most labour-intensive. Similar findings are reported from India, Korea and Japan. In some cases positive relationships are detected in some industries, or in some limited size ranges, but not elsewhere. Findings from Ghana, Kenya, and Zimbabwe (Biggs, Shah and Srivastava 1996), seem to conform better to the presumed relationships. The capital-labour ratios increase dramatically when moving up from the smallest size classes (1-19 workers). For firms with more than 20 employees, the relationship is considerably weaker and not much different from what was found in Asia. Thus, the exceptions to the rule of a positive correlation appear almost as frequent as the rule itself.

Another typical finding is that patterns visible at aggregate levels seldom survive disaggregation. For example, in Korea, the lowest labour intensities were found equally often in the 5-50 worker range as in the range from 50 upward, a pattern not observed at aggregate levels. In India, however, factories in the range of 10-49 workers were more labour-intensive than larger ones also after disaggregation.

Unfortunately, most studies exclusively use labour as size proxy, thereby excluding the possibility that capital-labour ratios vary systematically with capital or output. The Indian study is an exception and shows that capital-intensity varies positively and much stronger with capital than with workers. For two of the five surveyed industries, the ratio initially rises and then falls, suggesting an inverted-∪-shaped relationship. The variations are as large between as within industries.

Taken together, the evidence is not as unambiguous as one might expect. There are *tendencies* of increasing capital-intensity with firm size, but exceptions occur frequently, especially at disaggregated levels. Also, the tendencies are stronger with size defined as the value of the capital stock rather than as the number of workers.

Factor intensities in Kenyan manufacturing

The data in this study are drawn from the World Bank project ‘Regional Programme of Enterprise Development’ (RPED) and consists of an unbalanced panel of over 200 firms observed 1992-1994. Given the profound differences between formal and informal firms, I confine attention here only to the 195 formal establishments (450 observations). Variable definitions are given in table A1 in the Appendix and descriptive statistics of the variables are reported in table 1.

Table 1. Descriptive statistics of the variables used in the analysis. Only formal firms. The number of observations is 450.

Variable	*Median*	*Mean*	*Std Dev*	*Min*	*Max*
Output (Y)	14,300	61,121	128,140	21	1,150,000
Capital (K)	9,726	62,981	189,995	37	2,500,000
Unskilled workers (U)	30	102	281	0	3,331
Skilled workers (S)	11	34	120	0	2,172
$S + U = L$	50	136	344	1	4,000
Skilled wage (w_s)	38	57	59	14	600
Unskilled wage (w_u)	29	35	25	8	318
Profits (π)	1,000	8,856	27,033	0	305,600

NOTE: Capital (K) and output (Y) measured in thousands of Kenyan Shillings (KSh). 1 USD ≈ 36Ksh

As evident by the differences of the max and min values, the sample covers a wide size range. In addition, the size distribution is fairly thin towards the right tail, which explains the fact that the means are much higher than the medians.

Factor intensities at the aggregate level for different size categories are displayed in table 2 below. The size groups are based on three different variables: labour, capital and output, and are designed to approximately include one third of the observations each. Because of the skewness and poor accuracy of the capital variable, medians are preferred over means.

In general, capital-intensity is positively related to labour and even stronger so to capital and output. The largest worker category ($L > 75$) employs about twice as much capital per worker (K/L) as the smallest category. In Biggs, Shah and Srivastava (1996), the K/L –ratio increases four to nine times when moving from the smallest to the largest size group. In Little, Mazumdar and Page (1987), the same increase is two to ten times.[1]

The differences in capital-intensity between the smallest and largest establishments in terms of capital and output are considerably larger and rise by factors of eight and three, respectively.

[1] However, these studies and mine are not really comparable because we all use different size intervals.

Table 2. Median factor intensities in four Kenyan manufacturing industries. Only formal firms unless otherwise stated.

Firm category	*Obs.*	*K/L*	*K/S*	*K/U*	*S/L*
$L \leq 20$	135	179	380	291	0.43
$20 < L \leq 75$	166	192	865	319	0.25
$L > 75$	149	328	1,900	448	0.18
$K < 3{,}500$	145	75	214	129	0.43
$3{,}500 < K < 25{,}000$	151	217	816	302	0.26
$K > 25{,}000$	154	602	3,333	845	0.20
$Y < 6{,}000$	151	150	369	250	0.43
$6{,}000 < Y < 40{,}000$	172	192	810	313	0.27
$Y > 40{,}000$	127	476	2,832	632	0.19
Food	121	302	1,584	409	0.17
Wood	116	155	506	209	0.32
Textiles	108	148	400	315	0.46
Metal	105	484	1,629	706	0.25
Formal	450	226	972	374	0.25
Informal	166	17	26	30	0.50

NOTE: Capital (K) and output (Y) measured in thousands of KSh.

The skill ratio, *S*/*L*, drops from 40% to 20% from the smallest to the largest group, a pattern not observed in the Indian study. This is potentially interesting because it may indicate that larger firms in Kenyan manufacturing substitute capital for skill. It could also mean that the skill requirements per worker in larger companies are lower because of more specialised production processes in which every worker only need to command a narrow set of activities.

Factor intensities at the sub-sector level are presented in table A2 in the appendix. Some patterns observed in the aggregate case disappear. Capital-intensity increases with labour and output in food and textiles, but not in wood and metals. Sorted by size of the capital stock, however, the aggregated findings transfer nicely to the disaggregated case: capital-intensity rises uniformly with capital in all four sectors. The skill ratio falls with size in all sectors but food.

The Kenyan evidence thus conforms well to the studies above. Also here there are *tendencies*, possibly stronger than in these studies, of a positive relationship between capital-intensity and firm size. The relationship is stronger with capital as the size variable and sensitive to disaggregation (when size is defined as labour or output).

Why do factor intensities vary across firms?

A definite answer is beyond my ambitions here. There are simply too many potential causes, including issues related to production technology, firm behaviour, and the structure of factor markets, which may work individually or jointly together. Five possible causes deserve mentioning.

First, relative factor prices may vary systematically with firm size, presumably in the direction argued for in the introductory section. Second, the technology can be non-homothetic, so that firms choose input bundles which become progressively more intensive in some factor as output expands under constant prices. Third, firms may not share the same production function within an industry. This could be the result of a too broadly defined sector, in which the production processes are too diverse to be adequately approximated by a production function. If so, differences in relative factor intensities between firms can equally well be an outcome of different production technologies as of anything else.

Fourth, some firms may not maximise profits or minimise costs. This could be due to poor information, ignorance, or some alternative objective pursued by the firms. Fifth, risk attitudes can differ among firms. For example, if small firms were more risk-averse than larger firms, they would employ relatively more of those inputs that can easily be scaled down in the short-run if demand suddenly falls. The more variable input in developing countries is doubtless labour, so risk-averse firms would therefore use more labour per capital than their less risk-averse competitors.

The last two explanations are not addressed in the paper. The other issues, on the other hand, are considered to various extents. The presence of markedly diverse technologies can be handled by splitting the sample into sub-sectors of firms believed to be sufficiently similar to justify the assumption of a single production function. In practise, too much splitting produces lots of samples with few observations yielding unstable and imprecise parameter estimates: the appropriate level of aggregation must therefore be based on a trade-off between flexibility and precision. Variations in factor prices can be measured indirectly using estimated production functions if one maintains the assumption of them being related to their marginal products. Homotheticity can be tested as a restriction of sets of parameters of the translog production function.

Some direct information on factor prices is presented in table 3. Wages rise with all size variables. Clearly, wages are functions of several factors else than size, but in a recent study an isolated and significant positive size effect remains after controlling for a number of these (Manda 1997). Similar evidence is reported by Velenchik (1997) for Zimbabwe and by Teal (1996) for Ghana.

Table 3. Medians wages and profit rates. Firm-level wage rates are medians of mean yearly wages for the individual workers employed by the firm. Profits are gross profits before depreciation and tax.

Firm category	*Skilled wage*	*Unskilled wage*	*Profit/Capital*
$L \leq 20$	34	25	0.08
$20 < L \leq 75$	36	29	0.18
$L > 75$	58	38	0.10
$K < 3{,}500$	30	25	0.22
$3{,}500 < K < 25{,}000$	36	29	0.16
$K > 25{,}000$	57	36	0.06
$Y < 6{,}000$	30	24	0.08
$6{,}000 < Y <40{,}000$	40	30	0.14
$Y > 40{,}000$	63	37	0.14

NOTE: Capital (K), output (Y) and wages are measured in thousands of 1992 KSh.

A proxy for the user cost of capital, profit over capital, is reported in the right column of the table. Since the profit variable reported in the data reflects revenue less direct and indirect costs, which do not usually include costs for capital, it proxies the user cost of capital given a competitive environment. This assumption can certainly be challenged, but no better alternative exists given the data limitations. The proxy does not generally fall with size as argued by the literature, but rises, suggesting that relative prices of capital and labour be about the same for all size groups. Thus, if these figures were correct, there would be no reason to expect a relationship between capital intensity and firm size provided that the technology is homothetic, for reasons spelled out below.

3. Factor intensities and technology

Cost-minimising behaviour induce firms to chose inputs so that the technical rate of substitution (TRS) between inputs *i* and *j* equal their relative price. Throughout the paper, I adhere to Varian's (1992) formulation of TRS_{ij}, and define it as the ratio of the marginal product of input *i* to the marginal product of input *j*. It is interpreted as the rate at which input *j* can be substituted for input *i* holding output constant. Graphically, cost minimising firms choose inputs according to the tangency point of the isoquant and the price line. The locus of all tangency points given fixed relative factor prices defines the expansion path of a technology, which describes optimal input bundles for all positive outputs. In other words, the expansion path combines all points for which TRS is equal to some constant. Two possible expansion paths, **R** and **R'**, are depicted in the figures 1 and 2 below. **R** is a straight line from the origin, implying constant factor ratios and a homothetic technology. **R'** curves upwards, implying varying factor ratios and a non-homothetic technology. A function $f(x)$ is homothetic if it can be expressed as $f(x) = g(h(x))$, where g is positive monotone transformation of a linearly homogenous function h.

The non-homothetic technology in figure 2 bends off towards the capital axis. Thus, firms would choose progressively more capital-intensive techniques as output expands. Pack (1982 and 1976) and others advance the argument that expansion paths in manufacturing industries in Kenya and elsewhere in the third world actually bend off in this direction. The argument is based on the extent of mechanisation of activities that takes place outside the actual processing, such as packing and labelling, that is uneconomic at small scales. Indeed, these types of activities usually absorb significant shares of total costs in manufacturing industries. Likewise, processing itself may exhibit substantial indivisibilities of this kind, especially in mechanical engineering. It is not by any means unlikely that similar phenomena occur among the firms analysed here.

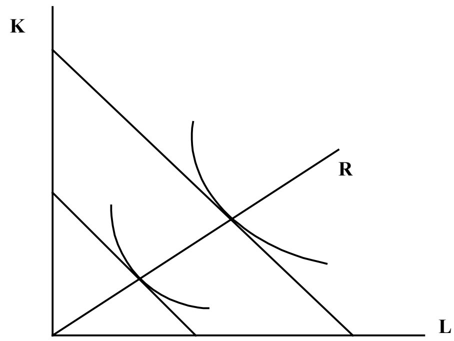

Figure 1. Homotheticity.

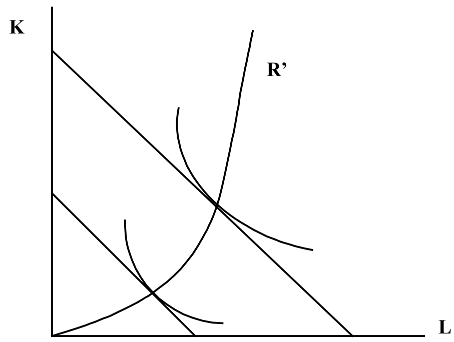

Figure 2. Non-homotheticity.

4. Model and estimation

Estimation of TRS and substitution elasticities while allowing for non-homotheticity requires a flexible specification of the technology. A translog production function is chosen for this purpose.

The translog production function

The analysis is based on a three-factor translog production function where output Y is modelled as a function f of inputs X_i,

$$Y = f(X) = \exp\left\{\beta_0 + \sum_i \beta_i \ln X_i + \sum_{i \le j}\sum \beta_{ij} \ln X_i \ln X_j\right\}, \qquad (1)$$

where i,j=1,2,3 are the previously defined inputs K, S and U. Raw materials and energy are not included in the analysis due to poor measurement. Their exclusion does not affect the parameters provided they enter the production process in fixed proportions with output and that they are not substitutable with the other inputs. I maintain this assumption and do not attempt to formally test its validity, given the data limitations.

The elasticity of input i with respect to output, e_i, is

$$e_i = \frac{\partial \ln f(X)}{\partial \ln X_i} = \beta_i + 2\beta_{ii} \ln X_i + \sum_{j \ne i} \beta_{ij} \ln X_j \,. \qquad (2)$$

The marginal product of the same input is

$$\begin{aligned} f_i = \frac{\partial f(X)}{\partial X_i} &= \left[\frac{\beta_i}{X_i} + \frac{2\beta_{ii} \ln X_i}{X_i} + \sum_{j \ne i} \beta_{ij} \frac{\ln X_j}{X_i}\right] \cdot f(X) \\ &= e_i \cdot \frac{f(X)}{X_i}. \end{aligned} \qquad (3)$$

The TRS$_{ij}$ is defined as the ratio of the marginal products, f_i / f_j .[2] The translog production function is homothetic if $\sum_j \beta_{ij} = 0$, which can be tested as a linear restriction on the estimated parameters.

The translog production function is a popular tool in the analysis of production because of its flexibility and ability to approximate a number of unknown underlying technologies. The flexibility comes at a cost, however, because nothing prevents the estimated model to violate the regularity conditions of a production function. The most important of these are non-negative marginal products (monotonicity) and convex isoquants. The latter

[2] Throughout the presentation we omit the negative sign. Thus, TRS becomes positive for well-behaved production technologies and equals the relative factor price for cost-minimising establishments.

condition holds only if the production function is quasi-concave, which it is if the bordered Hessian of first and second derivatives is negative semi-definite. The relevant derivatives and matrix for these tests are presented in Appendix B. Monotonicity and quasi-concavity are tested at each observation point for the estimated translog production functions. The conditions are rarely fulfilled globally in empirical work, but if they are met for a sufficient number of the observed data points, it is considered 'well-behaved' and interpretable (Berndt and Christensen, 1973). Global quasi-concavity can be imposed as a restriction of the parameters, but in the process one also imposes a number of unattractive restrictions, including unitary substitutability between all pairs of inputs (Lau 1978).

Estimation

The parameters of the translog production function in (1) can be estimated individually as a single equation or together with additional cost share equations as a system.

The perhaps-simplest single-equation estimation technique is OLS, which is used in a number of studies.[3] A potential problem associated with this approach is that the parameter estimates may be subject to some simultaneity bias because inputs hardly can be regarded as truly exogenous variables. Indeed, the micro-economic theory of the firm rests on the belief that inputs are *controlled* by the decision-maker in order to achieve some objective. If this is regarded as a problem one might opt for using instrumental variable techniques. Finding suitable instrumental variables is, however, a challenging endeavour. Some studies consider it so difficult as to motivate the use of the simpler OLS

[3] For example, Corbo and Mellor (1979), Deolalikar and Vijverberg (1987), and Biggs, Shah and Srivastava (1996), and several others.

approach.[4] Clearly, lagged values of the inputs could serve as instruments but that would reduce the sample size considerably for short and unbalanced panels. Moreover, lagged inputs may be so correlated with actual inputs that the OLS- and IV-results are almost the same (Corbo and Mellor 1979). In any case, the direction of the potential bias of the OLS-estimator is hard to foretell. In addition, under certain assumptions, including maximisation of expected profits and independence between the 'human' errors in the maximisation process and the errors arising the stochastic nature of production, OLS is still consistent and unbiased (Zellner, Kmenta and Dreze, 1966).

The systems approach was proposed by Berndt and Christensen (1973) and involves the joint estimation of the production function (1) and a set of input share equations, defined by

$$\frac{w_i X_i}{C} = e_i \,, \tag{4}$$

where w_i is the price of input i = 1,2,3 and C is total costs, respectively. Equation (4) states equality between input i's share of total cost and its elasticity. This is true under constant returns to scale with output fixed from the point of view of a producer that minimises costs in a competitive environment (Jorgenson 1993). The assumption of competitive markets is necessary to

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[4] A partial list of citations from these studies is illustrative:

".., the single-equation formulation may lead to simultaneity bias in the estimated coefficients if any [inputs] are determined jointly with value added. ---…, there are no obvious solutions to these problems but structural interpretation of this reduced-form relationship should be avoided." (Biggs, Shah, and Srivastava 1995, p 52f);

"Estimation of a production function may suffer from simultaneous equation bias, as the inputs may be simultaneously determined with output. If so, conclusions … are affected. --- [However, due to insufficient data,] we … utilize the direct production function approach…." (Deolalikar and Vijverberg 1987, p 295);

"A difficulty with the use of [OLS] is that the regressors (the factor quantities) are endogenous variables for an establishment within an industry. --- In such a case the [OLS] estimates … are biased and inconsistent. Consistent estimates could be obtained by using an instrumental variable (IV) estimator. In our case ---, there was no variable which could be used as an instrument. Therefore, we have estimated our model using [OLS] and thus our results may be subject to some simultaneous bias." (Corbo and Mellor 1979, p 198f).

ensure that the firm is a price-taker: it does not rule out the possibility that they face different input prices. It is not unlikely that such prices vary across firms is in a developing country like Kenya. Interest rates paid by companies certainly differ among firms if lenders charge extra for some expected firm-specific risk of default. The system consisting of (1) and the set of equations defined by (4), all with mean-zero error terms attached, can be estimated after dropping one of the share equations to obtain a non-singular system using ITSUR.[5] It main advantage lies in improved efficiency vis-à-vis equation by equation estimation because it accounts for covariances of the errors across models.

The estimation approach above has been employed in a number of studies, including the one by Little, Mazumdar and Page (1987), but has also been criticised by Kim (1992) because of the assumption of constant returns to scale.[6] In previous work on these data, estimates of the returns to scale are close to one and the assumption is therefore not felt to be very restrictive. On the other hand, if a translog production function is globally exhibiting constant returns, it is also homogenous and homothetic, which would make it useless for our purposes. However, there is nothing that prevents the translog from being of approximately constant returns locally, but not globally. Hence, it can be argued that the system above preserves the flexibility that motivated its choice from the beginning.

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[5] ITSUR (ITerative Seemingly Unrelated Regressions) is a development of Zellner's original invention (Zellner 1962, 1963). As the name suggests, the approach involves repeated use of SUR estimates of the parameters in the system to obtain new sets of residuals that are utilised to estimate the variances and covariances of the errors among the equations. The procedure is iterated until changes in the estimate of the disturbance covariance matrix become arbitrarily small. It yields parameter estimates that are numerically equivalent to those of the maximum likelihood estimator (Oberhofer and Kmenta 1974, Barten, 1968, cited in Berndt and Christensen, 1973). This feature is attractive because, in contrast to the original SUR estimator, it makes the system invariant to which of the share equations that is dropped.

[6] Kim proposes a system consisting of (1) and an elaboration of (4), given by: $w_i X_i / C = e_i \Big/ \sum e_i$, where the denominator is the returns to scale parameter. This specification produces very similar results to the one presented here for my data.

In Little, Mazumdar and Page (1987), the system approach is chosen in order to solve the 'problem' of endogenous inputs, but the argument is not compelling. Undoubtedly, the system does not model its endogenous variables in subsequent equations as in the conventional specification of simultaneous equations systems. Elsewhere, the system is typically motivated on efficiency grounds, since it includes the information contained in the first-order conditions for cost-minimisation, and not as a way to overcome potential simultaneity bias. I subscribe to the latter view and hence recognise that results obtained with the systems approach may be subject to some degree of simultaneity bias.

5. Results

Both the single-equation and the system approaches were adopted in the estimations of the translog production function. The guiding principle for model selection was compliance with the regularity conditions. On this basis, the systems approach outperformed the single-equation model, also when various panel methodologies were considered for the latter. The pitfall for almost all single-equation models was not monotonicity, most observations usually passed that particular test, but quasi-concavity, a condition seldom fulfilled by more than half of the observations. Since we are interested in TRS, convexity of the isoquants is essential, and we do not allow to many departures from it. With the systems approach, the share equations appear to 'pull' the marginal products to the positive region and in the process also make the production function locally quasi-concave for most observations.

The difficulty associated with having models to comply with quasi-concavity is troubling given the number of empirical applications of the translog production function. Recently, Salvanes and Tj∅tta (1996) discovered that one widely cited application of the translog cost function failed to comply with the regularity conditions. They hence argued that the conclusions reached in that study were dubious. Since the production function is no less difficult to estimate than a cost function, it is not implausible that some of the applications in the literature possess similar regularity problems.[7]

The preferred models estimated using ITSUR are presented in table A4. Both pooled and sector models are estimated to allow for different technologies among, but not within, sectors. The output and inputs are defined as above. Values of zero for one of the two labour input variables were replaced by 0.5, while at the same time deducting 0.5 from the other category, leaving the total number of workers the same. This procedure avoids having to drop 35 observations with zero inputs from the sample and is motivated by the belief that no establishment can operate without at least a small fraction of skilled or unskilled workers. The labour value shares are constructed as the wage cost per worker category divided by total costs for the three inputs. Total cost, in turn, is the sum of the wage costs for the two labour categories and the user cost of capital (r) times the capital stock. The user cost of capital is proxied by median profit rates evaluated by sector and size categories.[8] The errors in the system are assumed distributed according to a multivariate normal distribution.

The panel dimension is basically ignored in the analysis except for the inclusion of time dummy variables to capture intercept effects over the years. In principle, the system can be extended to accommodate random or fixed effects. The complexity of doing so within the current setting is, however, repelling, and the rewards uncertain. Since we are not focussing primarily on the precision of our estimates, the efficiency reason for exploiting the panel dimensions is not strong. Further, the panel is fairly short, only three years, and unbalanced. Hence, the estimates for individual effects and variances are likely to be poor. Unobserved heterogeneity among firms can certainly be present and so distort

[7] Most troubling is perhaps that researchers and referees usually are silent on the issue, which is surprising because the test for quasi-concavity is not difficult to implement. The test for the three-factor translog production function used in the paper is described in Appendix B and the relevant SAS-code appears in Appendix C.

[8] The main results hold also if medians of this variable are taken only by sizes or sectors.

the findings, but controlling for it efficiently given the data limitations is not easy. For these reasons, I do not use panel techniques.

Most of the parameter estimates in table A4 are statistically significant, and several are surprisingly similar across models. The R-squares hover around 0.7, which is a bit lower compared to the single-equation models.

The elasticities, evaluated at the medians of the involved variables 100 times using Monte Carlo simulations, differ across models. The capital elasticities range between 0.34 and 0.57. The elasticities for skilled and unskilled linger in the 0.17-0.37-interval. The elasticities for unskilled labour are systematically and significantly higher than for skilled labour. The returns to scale estimates are close to unity, but given the surprisingly low standard deviations increasing returns cannot be ruled out in the food and metal models (1.107 and 1.135, respectively). In contrast, textiles exhibits close to decreasing returns (0.954). In the better performing single-equation models as well as in other studies on the same data, capital elasticities are lower and labour elasticities higher. One may therefore suspect that the labour input shares are biased downwards to some extent, which in the process reduces the elasticities. In any case, the conclusions drawn are the same for the system presented here and for the better-performing single-equation models.

The rates of compliance with the regularity conditions are presented in table A3. Over 90% of the observations in all models are consistent with monotonicity. The performance in terms of quasi-concavity is less satisfactory: only in the pooled, textile and metal models are more than three-quarters of the observations passing this test. In wood and food are the compliance rates 53 and 63%, respectively. Thus, the estimated production functions are not strikingly well-behaved in all regions and some caution need be taken in the interpretations.

The last rows in table A4 report the results of Wald tests for Cobb-Douglas technology and homotheticity. In all models, the null hypotheses are strongly rejected.

The direction of the expansion paths

The finding that the production technology is not homothetic is important since it may indicate that Pack's argument that expansion paths arc off toward the capital axis is correct. Unfortunately, no analytical solution exists for the expansion path when the technology is defined by a translog production function. To provide a rough description of the direction it takes, factor ratios have been solved using the Newton-Raphson method in table 4 for three different output levels given median estimated TRS by respective model.

Table 4. Implied factor intensities for the estimated models for three output levels and constant TRS.

	Pooled	Food	Wood	Textiles	Metal
K/L					
$Y=$ 4,000	205	246	151	183	388
$Y=$ 12,000	216	267	213	110	450
$Y=$ 50,000	239	342	389	213	794
K/S					
$Y=$ 4,000	724	1269	1366	557	1371
$Y=$ 12,000	731	1226	466	353	1447
$Y=$ 50,000	736	1051	1520	241	1331
K/U					
$Y=$ 4,000	285	305	170	272	541
$Y=$ 12,000	307	342	394	159	654
$Y=$ 50,000	353	508	522	1867	1968
S/L					
$Y=$ 4,000	0.28	0.19	0.11	0.33	0.28
$Y=$ 12,000	0.30	0.22	0.46	0.31	0.31
$Y=$ 50,000	0.32	0.33	0.26	0.89	0.60

NOTE: Factor ratios are solved for three output levels given the median of the estimated TRS. Outputs and capital are measured in thousands of 1992 KSh.

The models display a substantial variation, but the overall picture is nevertheless quite clear: the expansion paths bend off toward the capital axis. Thus, firms would choose progressively more capital intensive factor bundles as they expand output, thereby supporting the Pack argument. The *K*/*L* ratios increase with every size category in all models except for the middle category in textiles. The pooled model suggests that firms with an output of 50 million KSh employ almost 20% more capital per worker than firms with an output of 4 million. The corresponding figures for wood and metal are substantially higher, 160 and 100%, respectively. In the food and wood models the differences are 40 and 15%.

The increases in capital intensity appear to be driven by a reduction of the relative amount of unskilled labour. This is evident from the *S*/*L*–ratio, which increases with firm size. The pattern is also reflected in the *K*/*S* and *K*/*U*–ratios: the former remains fairly constant whereas the latter increases firmly everywhere. Thus, larger firms appear to demand more skilled labour than smaller ones. The interpretation of this finding is not obvious, at least not from an economic-theoretical viewpoint. A possible explanation could be that the level of sophistication of both products and processing increases by size and so is more skill demanding.

Technical rate of substitution

The implied factor intensities in table 4 can be compared with the actual ones in tables 2 and A2. Except for metals, it seems that the capital intensities rise to a larger extent than motivated by the non-homotheticity of the technologies. Hence, non-homotheticity may not by itself wholly explain the positive relationship between capital intensity and firm size. Whether different relative factor prices explain the remaining part of this variation is therefore a relevant question. If firms minimise costs the relative factor price equal the associated TRS. Should these rates vary by size is it likely that also inputs prices vary accordingly. To investigate this, table 5 reports median TRS by output size groups.

The estimates are somewhat shaky across models and size groups. In the pooled and food models, TRS_{KS} falls by 50% and TRS_{KU} by 25% from the smallest to the largest class. In textiles the fall is dramatic and hardly reflecting the true relative factor price. More likely in this particular case is that the larger firms in the sector has not yet adjusted after the dramatic 50% reduction in output between the survey years and consequently operates with uneconomically large capital stocks. In metals, the rate moderately follows an inverted U-pattern, whereas in wood it goes in the opposite direction, suggesting that the relative price for capital *increases* considerably. The latter result is implausible and could be an effect of the estimations problems encountered with this sector. On the whole, the evidence in favour of the hypothesis that the relative price for capital is lower for larger firms is not compelling. There are indications of it in the pooled, food and textiles models, but not in wood and metal.

Table 5. Median TRS by firm size for different models.

TRS_{KS}[a]	Pooled	Food	Wood	Textiles	Metal
$Y < 6$	3.7	4.0	4.1	7.8	1.5
$6 < Y < 40$	2.7	3.0	5.1	1.8	1.9
$Y > 40$	1.8	2.1	6.8	0.7	1.3
TRS_{KU}[a]					
$Y < 6$	4.9	4.8	5.4	7.2	2.0
$6 < Y < 40$	4.7	5.0	8.2	3.5	2.8
$Y > 40$	3.4	3.9	10.4	1.3	2.4
TRS_{SU}[a]					
$Y < 6$	1.4	1.8	1.4	1.1	1.4
$6 < Y < 40$	1.8	1.7	1.5	1.3	1.6
$Y > 40$	1.8	1.8	0.9	2.1	1.8

a) Measured in millions of 1992 KSh per skilled or unskilled worker.

The estimated TRS_{SU} circle around 1.5, indicating that skilled labour is about 50% more productive than unskilled at the margin. There is no clear size pattern for this rate.

Elasticities of substitution

Two measures describing the ease by which one input can be substituted for another, i. e. the curvature of the isoquant, are estimated. The first is the direct elasticity of substitution, given by

$$\sigma_{ij}^{D} = \frac{f_i f_j (X_i f_i + X_j f_j)}{X_i X_j (f_{ii} f_j^2 - 2 f_{ij} f_i f_j + f_{jj} f_i^2)} \quad ,$$

which is interpreted as the percentage change in the factor ratio divided by the percentage change in TRS along the same isoquant. For regular technologies, σ_{ij}^{D} is always positive. In the case of more than two inputs, a more appropriate measure of elasticity of substitution between a pair of inputs must consider the effect of the other inputs. Such a measure is the well-known Allen partial elasticity of substitution, defined by

$$\sigma_{ij}^{A} = \frac{\sum_i X_i f_i}{X_i X_j} \cdot \frac{H_{ij}}{|H|} \quad ,$$

where $|H|$ is the determinant of the bordered Hessian matrix of the production function and H_{ij} is its *ij*'th cofactor. The measure is positive for substitutes and negative for complements.

These elasticities are evaluated at the medians of the involved variables 100 times using Monte Carlo simulations.[9] The means and standard deviations for the resulting populations are reported in table 6. The rankings of the elasticities are the same for both measures, although the absolute values are higher for the Allen elasticity of substitution. That is expected because σ_{ij}^{A}, unlike σ_{ij}^{D}, allows the other inputs to vary, which often reinforces the effect for inputs that are substitutes. In all models except textiles, skilled and unskilled labour exhibits considerably higher substitutability between each other than with capital. The differences in the Allen elasticities are statistically significant at the 10%-level in all models but textiles.[10] The least substitutable pair of inputs in all models except wood is capital and skill.

[9] The substitution elasticities were also evaluated at the medians by the three output size categories. These results are basically the same as the ones obtained using the overall medians and are therefore not reported.

[10] The σ_{SU}^{D}-measure is also significantly larger than the other elasticities in the pooled and food models.

Table 6. Elasticities of substitution between pairs of inputs, evaluated at the medians of the involved variables for different models.

Elasticity:	Pooled	Food	Wood	Textiles	Metal
σ_{KS}^{D}	1.471 (0.039)	1.492 (0.077)	1.96 (0.18)	1.412 (0.067)	1.49 (0.11)
σ_{KU}^{D}	1.596 (0.051)	1.607 (0.085)	1.76 (0.14)	1.60 (0.11)	1.710 (0.082)
σ_{SU}^{D}	1.872 (0.068)	2.13 (0.18)	2.12 (0.19)	1.456 (0.059)	2.03 (0.20)
σ_{KS}^{A}	1.200 (0.076)	0.920 (0.16)	1.90 (0.27)	1.34 (0.11)	1.03 (0.17)
σ_{KU}^{A}	1.578 (0.070)	1.61 (0.11)	1.65 (0.18)	1.69 (0.16)	1.72 (0.11)
σ_{SU}^{A}	2.33 (0.17)	3.30 (0.55)	2.47 (0.45)	1.45 (0.12)	2.88 (0.47)

NOTE: The elasticities were evaluated for median values of the inputs using Monte Carlo simulation with 100 replications. Means and standard deviations of the resulting population reported.

Clearly, these estimates are subject to a number of objections regarding estimation methodology, labour definitions and data accuracy. The classification of labour into two categories may not be consistent across firms, which could bias the skill-unskilled elasticity upwards. The groups, even if coherently defined, could be strongly heterogeneous and have the same effect. With these objections in mind, it is still surprising that the two labour groups are so easily substituted for each other. These results do not indicate that skill would be an overtly critical variable in production for Kenyan manufacturing firms. Hence, the Hamermesh claim that the main restriction on efficient production in LDCs is skill rather than capital is not supported.

7. Conclusions

As in a number of previous studies, I found, albeit with some exceptions, a positive relationship between firm size and capital intensity. The argument by Pack that this could be due to non-homothetic technologies was found to bear strong explanatory power. All estimated models reject homotheticity and predict that capital intensities increase by 20-160% along an arbitrarily chosen expansion path. But non-homothetic technologies only explain part of the story. There are some signs of falling relative capital prices with firm size, as indicated by falling TRS between capital and labour, but the results are somewhat shaky. It does nevertheless appear plausible that these two factors together, non-homotheticity and falling relative capital prices, explain most of the positive relationship between capital intensity and firm size.

Consequentially, if policy is to stimulate an increase in the demand for unskilled labour, it is not sufficient to level out factor price differences. In addition, small-scale production need to be expanded. However, the potential gains in *allocative* efficiency on a national level should be balanced against the probable losses in *technical* efficiency, since the latter has been shown to decrease with firm size (see papers 1 and 2).The net effect is, at best, uncertain. Hence, I would not argue that there exists a general case for the promotion of small-scale enterprises. One the other hand, there exists no strong case for constraining them either, which perhaps has been the actual policy pursued in several countries in Sub-Saharan Africa in recent decades.

Skilled and unskilled labour exhibit significantly higher substitutability between each other than with capital. This finding is certainly not consistent with the claim that skill would be a more serious constraint for manufacturing firms in LDCs than physical capital. If anything, it underlines the importance of the study of capital investment vis-à-vis that of skill formation. Clearly, these results hinge upon the accuracy of the skill variable and should therefore be interpreted cautiously.

Another striking finding are the difficulties encountered in having the translog production functions to be consistent with quasi-concavity. Concern was raised as to whether these problems only haunted me or if they are embedded in the approach altogether, in which case it is appropriate to issue a note of warning to all researchers working with translog functions: check for quasi-concavity!

The finding that manufacturing sectors display considerable non-homotheticity may have some implications for microeconomic theory of the firm where simple homothetic functional forms of the technology, such as the

Cobb-Douglas, commonly are used. Whether homotheticity simplifies matters without losing generality, or if it also affects the main results, is certainly an issue worthy of some attention.

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Appendix A: *Tables*

Table A1 Data definitions

Symbol	*Label*	*Definition*
Y	Output	The value of output produced in the year in 1992 prices
K	Physical capital	Replacement value of equipment and machinery in 1992 prices
S	Skilled labour	Managers, proprietors, engineers, physical scientists, accountants, economists, technicians, foremen, supervisors, and specifically skilled production workers
U	Unskilled labour	Semiskilled and unskilled production and ancillary workers
L	Total labour	$S + U$
w_s	Skilled wage	Median wage (per firm) for skilled workers
w_u	Unskilled wage	Median wage (per firm) for unskilled workers
π	Profits	Annual reported profit by the firm before tax and depreciation

Table A2. Median input factor ratios for firms in different worker intervals.

Firm category	*Obs*	*K/L*	*K/S*	*K/U*	*S/L*
Food					
$L \le 20$	35	250	853	365	0.20
$20 < L \le 75$	47	254	1,357	291	0.20
$L > 75$	39	515	2,791	635	0.15
Wood					
$L \le 20$	30	189	402	255	0.53
$20 < L \le 75$	47	119	476	195	0.31
$L > 75$	39	170	693	212	0.24
Textiles					
$L \le 20$	40	92	133	141	0.70
$20 < L \le 75$	35	143	543	349	0.49
$L > 75$	33	391	2,265	454	0.13
Metal					
$L \le 20$	30	538	1,333	869	0.30
$20 < L \le 75$	37	538	2,000	857	0.25
$L > 75$	38	357	1,905	496	0.21
Food					
$K < 3{,}500$	33	109	445	129	0.17
$3{,}500 < K < 25{,}000$	42	267	1,261	305	0.20
$K > 25{,}000$	46	733	5,597	859	0.16
Wood					
$K < 3{,}500$	41	64	136	97	0.50
$3{,}500 < K < 25{,}000$	50	167	566	259	0.32
$K > 25{,}000$	25	213	1,555	386	0.17
Textiles					
$K < 3{,}500$	52	73	125	150	0.67
$3{,}500 < K < 25{,}000$	25	194	543	313	0.46
$K > 25{,}000$	31	553	4,299	611	0.13
Metal					
$K < 3{,}500$	19	98	272	91	0.25
$3{,}500 < K < 25{,}000$	34	204	1,025	435	0.25
$K > 25{,}000$	52	790	3,333	1,225	0.26

NOTE: Capital (K) and output (Y) measured in thousands of KSh.

Table A2 (continued).

Firm category	*Obs*	*K/L*	*K/S*	*K/U*	*S/L*
Food					
$Y < 6{,}000$	31	174	679	256	0.15
$6{,}000 < Y < 40{,}000$	38	220	1,289	276	0.20
$Y > 40{,}000$	52	483	2,906	663	0.17
Wood					
$Y < 6{,}000$	47	150	403	250	0.43
$6{,}000 < Y < 40{,}000$	48	119	376	179	0.33
$Y > 40{,}000$	21	184	1,555	221	0.14
Textiles					
$Y < 6{,}000$	46	92	151	171	0.67
$6{,}000 < Y < 40{,}000$	44	182	724	361	0.37
$Y > 40{,}000$	18	529	4,817	722	0.14
Metal					
$Y < 6{,}000$	27	533	1,065	720	0.27
$6{,}000 < Y < 40{,}000$	42	335	1,254	491	0.26
$Y > 40{,}000$	36	753	3,333	1,110	0.22

NOTE: Capital (K) and output (Y) measured in thousands of KSh.

Table A3. Percentages of monotone and quasi-concave observations.

	Percent of observations with non-negative marginal products w r t			*Percent quasi-concave observations*
Model	*K*	*S*	*U*	
Pooled	100%	94%	96%	76%
Food	99%	93%	98%	64%
Wood	94%	91%	97%	53%
Textile	100%	95%	96%	79%
Metal	98%	99%	95%	83%

Table A4. ITSUR parameter estimates for the system defined by (1) and (4). Standard errors are given in parentheses with two digits. Parameter estimates are rounded to the same number of digits to the right of the decimal point.

Variable:	Pooled coeff/(s.e.)	Food coeff/(s.e.)	Wood coeff/(s.e.)	Textiles coeff/(s.e.)	Metal coeff/(s.e.)
Intercept	5.61	3.6	8.1	3.81	6.3
	(0.67)	(1.8)	(1.6)	(0.89)	(1.7)
ln K	-0.20	0.06	-1.05	0.28	-0.58
	(0.15)	(0.38)	(0.37)	(0.21)	(0.35)
ln (S)	0.587	0.531	0.773	0.650	0.546
	(0.027)	(0.049)	(0.059)	(0.049)	(0.071)
ln (U)	0.816	1.059	0.780	0.724	1.017
	(0.032)	(0.058)	(0.058)	(0.058)	(0.065)
$(\ln K)^2$	0.0568	0.051	0.116	0.025	0.080
	(0.0083)	(0.021)	(0.022)	(0.012)	(0.018)
$(\ln S)^2$	0.0504	0.0465	0.0660	0.0451	0.0524
	(0.0025)	(0.0043)	(0.0048)	(0.0046)	(0.0060)
$(\ln U)^2$	0.0662	0.0666	0.0647	0.0596	0.0820
	(0.0028)	(0.0052)	(0.0044)	(0.0054)	(0.0051)
$\ln K \times \ln S$	-0.0414	-0.0325	-0.0743	-0.0521	-0.0350
	(0.0038)	(0.0068)	(0.0082)	(0.0071)	(0.0089)
$\ln K \times \ln U$	-0.0835	-0.1072	-0.0844	-0.0785	-0.1050
	(0.0047)	(0.0084)	(0.0084)	(0.0090)	(0.0084)
$\ln S \times \ln U$	-0.0680	-0.0738	-0.0693	-0.0442	-0.0715
	(0.0038)	(0.0068)	(0.0068)	(0.0074)	(0.0083)
1993	0.04	-0.05	0.11	-0.20	0.17
	(0.11)	(0.23)	(0.21)	(0.21)	(0.22)
1994	0.02	0.18	0.06	-0.31	0.12
	(0.11)	(0.22)	(0.21)	(0.20)	(0.23)
Wood	-0.46				
	(0.13)				
Textile	-0.63				
	(0.13)				
Metal	-0.65				
	(0.13)				
Observations	450	121	116	108	105
R^2-*prod func*[a]	0.758	0.738	0.729	0.769	0.756
R^2-v_s-share[b]	0.628	0.627	0.709	0.664	0.488
R^2-v_u-share[b]	0.597	0.723	0.689	0.546	0.743
Elasticities[c]					
ε_K	0.464	0.575	0.505	0.337	0.569
	(0.025)	(0.055)	(0.052)	(0.039)	(0.053)
ε_S	0.2170	0.1661	0.219	0.293	0.200
	(0.0058)	(0.0092)	(0.010)	(0.013)	(0.012)
ε_U	0.3367	0.366	0.3048	0.323	0.367
	(0.0064)	(0.011)	(0.0090)	(0.014)	(0.011)
$\sum \varepsilon_i$	1.018	1.107	1.029	0.954	1.135
	(0.025)	(0.050)	(0.052)	(0.036)	(0.053)
Tests[d]					
$\beta_{ij} = 0$	0.000	0.000	0.000	0.000	0.000
$\sum_j \beta_{ij} = 0$	0.000	0.000	0.000	0.000	0.000

a) The statistic refers to the production function in (1).
b) The statistics refer to the value share functions for S and U in (4).
c) Means and standard deviations of the elasticities evaluated at median values of the involved variables using Monte-Carlo simulations with 100 replications.
d) Probability values of the null are reported.

Appendix B: *Regularity conditions for the translog production function*

The regularity conditions utilise first and second derivatives of the production function defined in (1). The elasticities and marginal products are already defined in (2) and (3). Monotonicity requires that these be non-negative, which is the same as to say that output must not decrease when an input factor is increased.

The second and cross-derivatives are given by;

$$
\begin{aligned}
f_{ii} &= \frac{\partial^2 f(X)}{\partial X_i^2} \\
&= \left[-\frac{\beta_i}{X_i^2} + \frac{2\beta_{ii}}{X_i^2} - \frac{2\beta_{ii} \ln X_i}{X_i^2} - \sum_{j \neq i} \beta_{ij} \frac{\ln X_j}{X_i^2} \right] \cdot f(X) \\
&\qquad + \left[\frac{\beta_i}{X_i} + \frac{2\beta_{ii} \ln X_i}{X_i} + \sum_{j \neq i} \beta_{ij} \frac{\ln X_j}{X_i} \right] \cdot e_i \cdot \frac{f(X)}{X_i} \\
&= \left(\beta_{ii} - e_i + e_i{}^2 \right) \cdot \frac{f(X)}{X_i^2} \quad ,
\end{aligned}
$$

and

$$
\begin{aligned}
f_{ir} &= \frac{\partial^2 f(X)}{\partial X_i \partial X_r} \\
&= \frac{\beta_{ir}}{X_i X_r} \cdot f(X) + \left[\frac{\beta_i}{X_i} + \frac{2\beta_{ii} \ln X_i}{X_i} + \sum_{j \neq i} \beta_{ij} \frac{\ln X_j}{X_i} \right] \\
&\qquad \times \left[\frac{\beta_r}{X_r} + \frac{2\beta_{rr} \ln X_r}{X_r} + \sum_{j \neq r} \beta_{irj} \frac{\ln X_j}{X_r} \right] \cdot f(X) \\
&= \left(\beta_{ir} + e_i \cdot e_r \right) \cdot \frac{f(X)}{X_i X_r} \quad .
\end{aligned}
$$

A function is quasi-concave if its upper contour sets are convex. The function itself need not be concave, in fact it can be convex, or locally both concave and convex. In terms of the production function, the latter case means that there may exist regions with increasing and regions with decreasing returns to scale.

The upper contour sets, here equivalent to the isoquants, are still convex. Since the objective of this paper is to evaluate TRS and substitution elasticities, we do not allow non-convex isoquants, in which case these measures become uninterpretable.

For a twice-differentiable quasi-concave function, the principal minors of the associated bordered Hessian, in our case defined by

$$H = \begin{bmatrix} 0 & f_K & f_S & f_U \\ f_K & f_{KK} & f_{KK} & f_{KS} \\ f_S & f_{KS} & f_{SS} & f_{SU} \\ f_U & f_{KU} & f_{SU} & f_{UU} \end{bmatrix},$$

should alternate in sign. Equivalently, the condition can be expressed as $(-1)^r D_r > 0$, $r = 1,2,3$, where D_r is the r^{th} principal minor. These are

$$(-1)^1 D_1 = (-1) - f_{KK}^2 = f_{KK}^2 > 0$$

$$(-1)^2 D_2 = -f_K^2 f_{SS} + 2 f_K f_S f_{KS} - f_S^2 f_{KK} > 0$$

$$\begin{aligned}(-1)^3 D_3 = (-1) \cdot (&-f_K^2 f_{SS} f_{UU} + f_K^2 f_{SU}^2 + 2 f_K f_{KS} f_S f_{UU} - 2 f_K f_{KS} f_U f_{SU} \\ &- 2 f_K f_{KU} f_S f_{SU} + 2 f_K f_{KU} f_U f_{SS} - f_{KK} f_S^2 f_{UU} + 2 f_S f_{KK} f_U f_{SU} \\ &+ f_S^2 f_{KU}^2 - 2 f_S f_{KU} f_U f_{KS} - f_{KK} f_U^2 f_{SS} + f_U^2 f_{KS}^2) \\ &> 0\end{aligned}$$

Since the derivatives are functions of both parameters and observed inputs, the test is conducted on each data point. We wish to have a defendable majority of the observations to comply with this condition.

Appendix C: *SAS - code*

The program below checks monotonicity and quasi-concavity for a predefined data set `karl` containing variables and parameters. The variables `ly`, `lk`, `s` and `u` denote natural logarithms of the variables *Y, K, S* and *U* defined in the text above. `k`, `ls` and `lu` represent their levels. The beta coefficients begin with `b`. Elasticities and derivatives are labelled as in the text above. Proportions of the observations that fulfil the regularity conditions are reported. For example, *monok* is the proportion of positive capital marginal products. *qcon* is the proportion of locally quasi-concave observations. Anyone who finds the program useful can use it freely.

```
data p; set karl;

*** defining elasticites ***;
 ek =      bk+2*bkk*lk+bks*s+bku*u;
 es =      bs+2*bss*s+bks*lk+bsu*u;
 eu =      bu+2*buu*u+bku*lk+bsu*s;

*** defining first derivatives ***;
 fk =      ek*(Y/k);
 fs =      es*(Y/ls);
 fu =      eu*(Y/lu);

*** defining second derivatives ***;
 fkk =      (bkk-ek+ek*ek)*(Y/(k*k));
 fss =      (bss-es+es*es)*(Y/(ls*ls));
 fuu =      (buu-eu+eu*eu)*(Y/(lu*lu));

*** defining  cross derivatives ***;
 fks =      (bks+ek*es)*(Y/(k*ls));
 fku =      (bku+ek*eu)*(Y/(k*lu));
 fsu =      (bsu+es*eu)*(Y/(ls*lu));

*** Principal minor determinants of bordered Hessian  ***;
 D2 =      - fk*fk*fss + 2*fk*fs*fks - fs*fs*fkk;
 D3 =       (-1)*
( -   fk*fk*fss*fuu +   fk*fk*fsu*fsu + 2*fk*fks*fs*fuu  - 2*fk*fks*fu*fsu
  - 2*fk*fku*fs*fsu + 2*fk*fku*fu*fss -   fkk*fs*fs*fuu  + 2*fs*fkk*fu*fsu
  +   fs*fs*fku*fku - 2*fs*fku*fu*fks -   fkk*fu*fu*fss  +
fu*fu*fks*fks);

*** checking monotonicity and quasi-concavity***;
 if ek ge 0 then monok=1;       else monok=0; if ek=. then monok=.;
 if es ge 0 then monos=1;       else monos=0; if es=. then monos=.;
 if eu ge 0 then monou=1;       else monou=0; if eu=. then monou=.;
 if D2 ge 0 and D3 ge 0 then qcon=1; else qcon=0;       Dx=D2*D3;
 if Dx = .              then qcon=.;

*** output: regularity conditions ***;
proc means; var ek es eu monok monos monou qcon;    run;
```

PERFORMANCE OF FOUR KENYAN MANUFACTURING INDUSTRIES: 1992-94

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Abstract: The performance of the food, wood, textile and metal sectors in Kenyan 1992-94 is analysed in terms of technical efficiency and productivity using fixed- and random-effects Cobb-Douglas production functions. Small and informal firms are comparably inefficient. Food, followed by metals, is the most productive sector. Growing firms are more productive than contracting ones, suggesting that high turnover may increase overall sector productivity. Several variables do not explain the variation in productivity, including exporting, skill, access to overdraft facility and foreign ownership. Textiles appear to have experienced severe technological regress after the trade liberalisation.

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1. Introduction

We shall in this paper analyse the performance of the four manufacturing sectors included in the Kenyan RPED-survey in terms of technical efficiency and productivity. The long-term trends of these variables are analysed elsewhere (Chapter 2, Bigsten and Kimuyu 1998): here we are primarily interested in their behaviour during the survey years, and how they vary across sectors and among different categories of firms. We will also attempt to unveil some of the underlying factors behind the variation in performance. Since our analysis is confined to Kenyan firms alone, we cannot say anything conclusive about the impact of general factors such as corruption, infrastructure, institutional inefficiency and low demand simply because these are more likely to affect the overall level of performance, and not its variation among firms. Our focus is therefore on firm-specific variables, including location, age, growth, human capital, export behaviour, credit access and ownership. We base the selection of these factors on both theoretical and Kenya-specific empirical grounds. For policy considerations, the relative importance of these variables are of interest, and we draw some conclusions with this in mind in the final section of the paper.

The next section contains a brief overview of the main efficiency constraints for manufacturing production in Kenya since Independence. Section 3 presents the variables used in the empirical analysis in the later sections and evaluates partial factor productivities for different firm sizes. Estimation of technical efficiency using fixed effects- and stochastic frontier-models are conducted in section 4, which suggest considerable variation in technical efficiency and productivity across firms. Potential determinants for firm-specific productivity are discussed in section 5 and analysed in section 6 using average production functions. The paper ends with a short summary and some conclusions in section 7.

2. Background

The rise in the share of manufacturing in total output and employment and a corresponding decline in agriculture is usually considered necessary for economic development of countries such as Kenya. The industrial structure that evolved in Kenya was however geared to the small domestic market with some limited targeting of the regional market in the Eastern African region. Import substitution was therefore the main focus of industrial policy from the colonial period through to the first two post-colonial decades and thus prescribed the scope of the industrial development that occurred.

Both the colonial and the post-colonial governments promoted the domestic manufacturing sector in a variety of ways. The structure of taxes and several price regulations, ranging from wages to input price policies, favoured the manufacturing sector. A number of financial and development organisations were also established to foster the growth of industry. The post-colonial government went even further, and chose to invest in manufacturing establishments. The governments of both regimes pursued protective trade policies to promote the establishment of domestic industries. Both tariffs and quantitative restrictions were applied. To attract foreign capital, a wide range of incentives was also instituted. Thus an inward oriented industrial structure emerged. That such protection results in inefficient industries characterised by low productivity due to the absence of competition is an established fact (Granér and Isaksson 1998). The abilities of the industries to penetrate export markets were consequently constrained.

The rate of expansion of industry therefore became dependent on the growth of domestic demand. The limited size of the domestic market meant that scale economies, where these were technologically feasible, could not be realised. As the constraints to industrial growth due to the limits of the domestic market became clearer to policy makers, the need for export orientation was appreciated and increasingly promoted. The domestic industries, which had evolved in such a protected environment, were however ill-prepared to face the competition in the world markets. The trade liberalisation policies, followed under the World Bank and IMF sponsored structural adjustment programs dating from the 1980s, which meant that the domestic manufacturers faced increasing competition from imports, made this abundantly clear. This is precisely the key problem facing the manufacturing sector. The low productivity that characterised most industries in the previous protective regimes left the sector ill-prepared for the new competitive pressures in the post-liberalisation period. Low productivity translates into high unit costs, which explain the competitive disadvantage in both the domestic and foreign markets.

The appropriate post liberalisation industrial strategy entails transformation from the historical inward to an outward orientation, with exports as the driving force. This is the core of Kenya's current industrial policy. It holds the promise of access to unlimited export demands, for such a small country, and thus the removal of demand side constraints to industrial growth, full capacity utilisation, technological advances, investment and growth. The export promotion hypothesis also has an efficiency component: exporting firms must be competitive, implying high technical efficiency and productivity relative to international standards. In a way, the RPED-data enable us to test this hypothesis explicitly as sectors with varying degree of export content of output are surveyed. For instance, the food sector has traditionally been the major export sector in comparison to wood, textiles and metal. Hence, if food is more productive than these other sectors, the efficiency-argument of exporting is supported.

Internally, the firms have to overcome the inefficiencies that developed in the protective regime to be able to expand into the larger export markets. The need for efficiency has become even more urgent also to maintain their traditional domestic markets against competing imports as the protective walls are removed in an increasingly liberalised imports regime. Efficiency is therefore important both for firms aiming to penetrate the export markets, and for those whose objectives are limited to the domestic markets. To survive the firms will have to develop their competitive strengths to match their foreign competitors in the domestic and export markets.

A major aim of this paper is therefore to analyse the structure of Kenya's manufacturing from the viewpoint of technical efficiency and productivity. These variables are considered important if not the crucial elements in establishing competitive strength to be able to face up to increased competition in the more liberalised environment. We believe that this is a precondition for industrial development of the economy.

Technical efficiency is an important issue in its own right in a world of scarce resources. In the introduction to his seminal paper, Farrell (1957) noted that "if economic planning is to concern itself with particular industries, it is important to know how far a given industry can be expected to increase its output by simply increasing its efficiency, without absorbing further resources". This is the principal motivation of this paper.

3. Data and partial factor productivities

The RPED data contain extensive firm-specific information related to production, which opens up a number of possibilities for analysing various aspects of production. Since we use the production function as our main tool in characterising the production process within firms, we need to carefully define and describe the output and input variables required for that analysis. This is done next, followed by an analysis of partial factor productivities. Econometric estimation of production functions is conducted in sections 4 and 6.

The definitions of the output and inputs are as follows. Output (Y) is the value of all output produced by the firm in a given year. Capital (K) is the replacement value of the machinery and equipment. Labour (L) is the total number of full-time workers including casuals involved in production during the year. Intermediate inputs (M) is the sum of the costs for raw materials and energy. Some of the variables contain substantial shares of missing values, which have been imputed by exploiting the panel dimension of the data set.[1] A small number of outliers are omitted from the analysis.

We expect the noise-to-signal ratio for the inputs and output to be comparatively high for a number of reasons. One is because of the problems associated with correctly measuring variables that vary over time, such as output and intermediate inputs. This problem is probably more serious for small firms, as argued by Liedholm and Mead (1987). Secondly, the value of output may be biased upwards due to varying degrees of market imperfections. A third reason is the difficulty of accurately valuing the capital stock, which typically consists of a wide range of different types of machinery and equipment acquired under long periods of time. A fourth potential cause for noise is unwillingness by the firms to reveal true values in fear this information reaches competitors or taxing authorities. A final source of data impreciseness originates from the conversion of nominal to real values of the variables. Sector-specific deflators are used for outputs, while the deflators for capital and intermediate inputs are assumed equal across sectors. Given the heterogeneity of the sample firms, even within sub-sectors, one would have preferred the use of firm-specific deflators, but such indices were neither available from public sources nor deductible from the data.

Having mentioned these limitations, we may now consider the descriptive statistics of these variables presented in table 1. A general observation for all variables is that their distributions are strongly skewed to the right. This is so despite the stratification of the sampling procedure in which larger and formal firms are over-represented. The use of weights has a tremendous impact on the means: the weighted means, which are roughly representative of the 'true' population, are only a fraction of the sample means. The difference of gross output and intermediate input (*Y-M*), gross value added, is negative for 22

[1] Missing entries of capital are imputed using previous or last period's value, correcting for the depreciation rate. Intermediate inputs is imputed by using its mean ratio to output in the periods for which the variable is reported. Output and labour are not imputed.

observations, which we interpret as indicative of inaccurate measurement primarily of the M –variable.[2]

Obscured in this table is the variation across firm categories. Naturally, the major difference occurs between formal and informal firms. For instance, the median number of workers among the sectors ranges from 40 to 51 in the formal sector in comparison with 2 to 5 in the informal sector. Among formal firms, the highest median output is recorded in the food sector, followed by metals. The largest median capital stock is recorded in metals, followed by food. Wood and textiles produce significantly less than these two sectors and operate smaller capital stocks.

Table 1. Summary statistics of output and inputs based on a sample of 615 (166 informal) observations on 266 firms (70 informal) in Kenyan manufacturing industries observed during 1993-1995.

	Mean	Weighted mean	Median	Std Dev	Minimum	Maximum
Y	45,632	2,109	5,400	113,811	4	1,150,000
K	47,130	1,099	3,500	167,556	1	2,500,000
L	102	6	22	301	1	4,000
M	24,543	1,165	1,916	68,366	0	905,250
$Y–M$	19,750	905	1,916	58,042	-43,409	764,940

NOTE: All variables except L measured in thousands of Kenyan Shillings.

Partial factor productivities and capital-labour ratios are presented in table 2 below. They describe the contribution of a single input to output, which, in turn, may identify potential gains to be made from reallocating inputs to activities, or firm types in which they are more productive. Such ratios can also reveal differences in factor intensities, which *could* be evidence of imperfections in factor markets, such as price discrimination. However, these measures say nothing conclusive about total factor productivity, nor do they inform us about a firm's technical efficiency.

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[2] Y is a single figure in the survey questionnaire, whereas M is a summary measure of all intermediate inputs, some of which the respondent had problems to recall accurately. For this reason, we believe that Y is measured with more precision than M.

Two measures of labour productivity are reported: the first is the simple output to the number of workers ratio (*Y/L*) and the second is the ratio of output to total wage cost (*Y/wL*). Both these measures display an inverted ∪-shaped relationship with firm size, peaking in the 76-500- and 21-75-worker intervals respectively. The increase in *Y/L* is more accentuated than the one in *Y/wL*, which most likely is an effect of the higher wages paid by larger firms (Kulundu Manda 1997). Also capital productivity (*Y/K*) and the capital-labour ratio reveal inverted ∪-shaped correlations. Another finding is that informal firms employ much less capital per employee than do formal firms. As a consequence capital productivity is higher, and labour productivity lower, for this category. Disaggregating the data into sub-sectors does not substantively alter these observations.

Table 2 Median relative factor productivities by size categories for the pooled sample.

Firm category	*Y/L*	*Y/wL*	*Y/K*	*K/L*
Informal	72	5.05	4.30	15
Formal, 1 – 5 workers	106	5.45	0.46	171
Formal, 6 – 20 workers	195	7.78	1.38	181
Formal, 21 – 75 workers	287	9.60	1.50	190
Formal, 76 – 500 workers	405	9.31	1.42	333
Formal, 500 + workers	187	8.63	0.82	260

NOTE: All values are expressed in thousands of Kenyan Shillings except *L*.

A short comparison with evidence from manufacturing sectors in other developing countries in Asia (Little, Mazumdar and Page 1987) and Africa (Biggs, Srivastava and Shah 1996) is instructive. Capital intensity generally increases with firm size, especially among African firms, although the smallest are not always the least capital intensive. Likewise, labour productivity increases with size in most cases, albeit not uniformly so, while capital productivity exhibits a less regular pattern, sometimes (in Thailand and South Korea) taking the form of the inverted-∪ detected above. In general terms, we may therefore conclude that our findings are broadly consistent with these studies, perhaps with the additional observation that the relationships in the Kenyan data are somewhat more stable.

As made clear above, one factor productivity that increases does not imply higher overall productivity, but if all factor productivities grow with firm size, it does. Indeed, this is the pattern we observe: firms in the 21-75-, or possibly in the 76-500-worker interval, appear more productive. The next section shall probe into the question of whether this is an effect of increasing returns to scale or a positive relationship between size and technical efficiency.

4. Productivity and technical efficiency

As discussed in the previous section, partial factor productivities are of limited usefulness in describing overall productivity of firms. Naturally, the concept of productivity refers to the ratio of output to input, which then by some index may be compared over time or across firms. The classical problem in productivity analysis is the case where there is more than one input: how should they be aggregated? A number of approaches exists, and the literature is rich in both theoretical contributions and empirical applications (see, for instance Fried, Lovell and Schmidt 1993). For our concerns, we have chosen the production function approach as the main tool of analysis. We motivate this choice on both flexibility and transparency grounds: a simple production function may easily be complemented with explanatory variables in order to explore the determinants of productivity. The production function also provides parameter coefficients, which are directly interpretable, and usually accommodates statistical noise. The more sophisticated non-parametric approaches do not share these attributes, although they have other attractive properties.

Technical efficiency is a distinct concept, not to be confused with productivity, although they are closely related. The term refers to the ratio of actual output to the maximum output feasible given inputs. The set of maximum output levels corresponding to all positive input combinations forms the production frontier, the outer edge of the production possibility set, which in our case is defined by a frontier production function. It follows that any pair-wise comparison of efficiencies among firms strictly depends on the shape of the estimated frontier. For example, there is nothing contradictory with a firm being both more productive and less efficient than another firm, which can happen if the firms differ in size and the technology exhibits non-constant returns to scale.

Hence, the scale property of the frontier production function is of great importance, especially if one wishes to make any statement about the size-efficiency relationship. As the estimates for returns to scale vary across different methodologies, it can sometimes be meaningful to impose the restriction of constant returns, a possibility considered below. Another important issue is on what level of aggregation firms are expected to share the same frontier production function. The approach taken in this section is to assume a single frontier for all sub-sectors, which carries the advantage of making inter-sectoral comparisons possible. Whether these differences really refer to technical efficiency can be questioned, however. In any case, they can certainly be interpreted as differences in productivity, which is the view taken below. The econometric models and the results are presented next.

Econometric models

The literature provides a number of methods for estimating technical efficiency. For our purposes, we have chosen to utilise two models: a fixed-effects (FE) model and a random effects (RE) model, in order to check the invariance of our results to the particular method selected. Both models provide estimates of the production model,

$$y_{it} = \alpha + \mathbf{x}_{it}\beta + v_{it} - u_i, \qquad (1)$$

where y_{it} is output; α is an intercept term; $\mathbf{x}_{it}$ is a vector of inputs; β is a vector of coefficients; v_{it} is a disturbance term assumed iid N(0, σ^2_v); and $u_i \geq 0$ is a technical *in*efficiency term assumed fixed in the FE- and random in the RE-model. The indices i=1,…, N and t=1,…, T refer to the firms and periods for which the observations were made, respectively. Motivated by the noisiness of the data and the short time span of the panel, we restrict technical efficiency to be time invariant.

In the FE-model, we retrieve the u_i's by first expressing (1) as deviations from individual means,

$$(y_{it} - \bar{y}_i) = (\mathbf{x}_{it} - \bar{\mathbf{x}}_i)\beta + (v_{it} - \bar{v}_i), \tag{2}$$

where the upper bar denotes individual means over time, and perform least squares on the resulting expression. This transformation removes the time invariant terms α and u_i. Secondly, we recover these parameters using,

$$\hat{\alpha} - \hat{u}_i = \hat{\alpha}_i = \bar{y}_i - \bar{\mathbf{x}}_i\hat{\beta}, \tag{3}$$

which is true because we assume the errors to average out to zero over time. In essence, this is the least squares dummy variable estimator. For a fully efficient firm, u_i=0, and therefore, $\hat{\alpha}_i = \hat{\alpha}$. Hence, we may finally compute the FE-estimates of the u_i's for the remaining firms using (Greene 1993),

$$\hat{u}_i = \max(\hat{\alpha}_i) - \hat{\alpha}_i. \tag{4}$$

This estimator is consistent in *T,* provided that also $\hat{\beta}$ is consistent, which holds as *N* goes to infinity (Greene 1993). Throughout these estimations, we will use the natural logarithms of output and inputs. The appropriate measure of technical efficiency (*TE*) of firm *i*, in accordance with the original Farrell (1957) concept, is therefore,

$$TE_i = \exp(-\hat{u}_i), \tag{5}$$

which is 1.00 for fully efficient firms and in the (0, 1)-interval for firms with some degree of technical inefficiency of production.

In the RE-model, we treat the u_i's in equation (1) as random, and we will assume that they are independent from the v_{it}'s and iid $|N(0, \sigma^2_u)|$ (which means that its distribution is truncated from below at zero to ensure non-negativity). This model is a special case of the model proposed by Battese and Coelli (1992) with the efficiency time trend parameter and the parameter for the mean of the truncated distribution of u_i restricted to zero. The parameters in (1) and the variance parameters, $\sigma^2 = \sigma_u^2 + \sigma_v^2$, and, $\gamma = \sigma_u^2 / \left(\sigma_u^2 + \sigma_v^2\right)$, are estimated using the method of maximum likelihood utilising the computer programme, FRONTIER 4.1b (Coelli 1994). The significance of the inefficiency effects can be tested using a likelihood ratio test of the γ-parameter. Firm-specific technical efficiencies are predicted by deriving expressions for the conditional expectation of the right-hand side in equation (5) conditional upon the observed value of (v_{it} - u_i) in the manner set forth by Battese and Coelli (1993).

The issue of whether u_i should be treated as fixed or random is by no means trivial. Both approaches have strengths and weaknesses. The FE-model permits the firm-specific effects to be correlated with the explanatory variables: the parameter estimates are still unbiased and consistent. Moreover, the errors need not be normal and if heteroscedasticity is present, the estimates remain consistent albeit inefficient. On the other hand the approach very sensitive to statistical noise. A single erroneous observation may have profound effects on the obtained efficiency scores. The RE-model explicitly accommodates the noise component, but produces biased and inconsistent estimates if the errors are not independent from the inputs. Furthermore, the predicted efficiencies of the RE-model have been shown to be very sensitive to heteroscedasticity in any of the two error terms (Caudill and Ford 1993). In light of this discussion, it is evident that restricting attention to only one methodology is potentially hazardous. We shall therefore consider both, and it is shown below that the main findings are robust to the choice of approach.

An additional difficulty concerns the potential endogeneity of inputs. If an input in (1) is endogenous, in the sense that it is a function of output, the estimated parameters are biased and inconsistent. The conventional way to solve this problem is to apply some type of IV-estimation technique, but for production functions appropriate instruments are rarely available. In a panel data setting, a natural instrument is lagged inputs, but it is doubtful whether such instruments are econometrically valid, especially so in our case because of the simultaneous presence of both growing and contracting firms. Earlier experience also suggests a momentous drop in efficiency by using this approach. Consequently, we have decided to estimate the production functions directly, acknowledging the fact that the parameter estimates may be subject to some unknown degree of simultaneity bias.

Results

The parameter estimates obtained from estimation of the FE- and the RE-models outlined above are presented in table 3. The production functions are restricted to the Cobb-Douglas form, motivated by its small number of parameters and the poor performance of the more flexible translog specification regarding compliance with the regularity conditions. Given our doubts about the accuracy of the *M*-variable, we specified *Y* as a function of *K*, *L* and *t* only, simply omitting that variable. Alternative specifications, such as *Y-M* as a function of *K*, *L* and *t*, or *Y* as a function of *K*, *L*, *M* and *t*, do not change the main conclusions drawn.

The FE-models are estimated using weighted OLS to correct for heteroscedasticity, not for the stratification of the sample.[3] Only pooled results are reported in order to make inter-sectoral productivity comparisons possible as mentioned above. Thus, we confine all firms to share the same technology, which is defendable because none of the estimated coefficients of the pooled model is significantly different from the ones obtained from the sub-sectors estimated individually. The only significant difference is the time variable in textiles, which is negative and significant at the 5%-level. We return to the interpretation of this result later.

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[3] Because all firms are assumed to share the same technology, defined by a production function, weighting the sample according to sampling probability would produce the same results asymptotically. If different strata of the sample have different slope parameters should separate production functions for these be estimated (Deaton 1997). Further, giving the small firms, for which the error variance is greater, larger weight would increase the problem of heteroscedasticity, which in the presented setting is solved by weighting up the larger firms.

Table 3. Parameter estimates of the fixed effects model (FE), the fixed-effects model with constant returns to scale imposed (FE-CRS), and the random effects model (RE).

	FE Coefficient (standard error)	FE-CRS Coefficient (standard error)	RE Coefficient (standard error)
Intercept	0.001 (0.017)	0.002 (0.017)	9.718 (0.329)
ln (K)	0.108 (0.031)	0.168 (0.031)	0.278 (0.029)
ln (L)	0.504 (0.063)	0.832 (0.031)	0.839 (0.056)
t	-0.037 (0.022)	-0.021 (0.022)	-0.026 (0.042)
σ^2			2.298 (0.255)
γ			0.715 (0.042)
Returns to scale	0.612	1.000	1.117
R-square	0.150	0.095	
Log-likelihood			-878.540
LR-test (a)			93.910
Observations (b)	555	555	615
Tests:			
CRS (c)	0.000		0.005
Homoscedasticity (d)	0.342	0.266	

a) This is a likelihood ratio test of the significance of γ. Critical value at the 5%-level with one degree of freedom is 2.71 (obtained from the mixed chi-square distribution in Table 1 in Kodde and Palm 1986).

b) The within transformation removes all firms that were only observed once. Hence, the number of observations is lower in the FE-models (555 compared to 615).

c) Probability of the null, ln(K)+ln(L)=1.00, being true according to the Wald test statistic.

d) Probability of the null of homoscedasticy according to White's test.

The parameter estimates for the inputs in table 3 are all significant and interpretable as input elasticities with respect to output because of the Cobb-Douglas functional form. The returns to scale, the sum of the input elasticities, of the unrestricted FE-model in the second column is remarkably low and significantly less than unity as indicated by the Wald test reported at the bottom of the column. Similar estimates on returns to scale are obtained by Roberts and Tybout (1997, table 5.3) who consider them too low to be plausible, and probably driven by sample noise.[4] We have therefore estimated a second FE-model imposing the restriction of constant returns to scale (FE-CRS).[5] In the RE-model, we find significantly increasing returns to scale: in comparison with the FE-CRS this is mainly driven by a significantly higher elasticity for capital.

Mean technical efficiencies are reported in table 4 below. For the FE-models these were calculated by replacing max($\hat{\alpha}_i$) with the 90th percentile, in the process defining the upper decentile (in terms of $\hat{\alpha}_i$) of firms as technically efficient. This is motivated by a desire to make the frontier 'less deterministic' because of the paramount influence a single large positive residual may have on overall efficiency scores. The use of the 90th percentile is certainly arbitrary, but all conclusions based on comparisons between firm categories remain irrespective of whether the 80th, 95th or 99th percentile is employed. The only change is a shift in the overall *level* of mean efficiencies. For this reason are quantitative comparisons among firms in terms of efficiency units somewhat precarious, whereas the qualitative differences are more certain. Given the similarity of mean efficiencies to those of the stochastic approach, however, we believe that the predicted efficiencies by the FE-models are roughly correct.

The cell means across firm categories reveal several interesting relationships. All models predict strongly positive size-efficiency relationships up to and including the 75-149-worker segment. For the largest size category, efficiency declines in the FE-CRS and RE-models, proposing a similar inverted ∪–shaped relationship as discovered in the previous section. This pattern does not occur in the FE-model, which we regard as a less likely result, probably driven by the unrealistically low returns to scale.

Informal firms are less efficient than formal ones in all models, although the magnitude of this difference varies considerably across models. The higher the

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[4] Deaton (1997, p108f) shows that measurement error in the explanatory variables constitutes a bias towards zero of within slope parameter estimates.

[5] We would certainly have favoured estimating the RE-model too with the same restriction, but this is not easily implementable with the current state of software.

estimated returns to scale, the less is this difference. In the FE- and FE-CRS-models, the differences are substantial whereas in the RE-model it is less than 10%. The small sizes and low capital-labour ratios of the informal firms probably cause this variation (see table 2), which locates them at the far corner of the production frontier hyperspace.

Table 4 Mean predicted technical efficiencies by firm categories for three different models. The number of observations in each cell for the fixed-effect models (Obs(FE)) and the random effects model (Obs (RE)) are reported for each cell.

Firm category:	Obs (FE)	FE	FE-CRS	Obs (RE)	RE
Informal	56	0.04	0.20	70	0.41
Formal	155	0.34	0.43	196	0.45
Formal, 1-5 workers	19	0.09	0.24	22	0.35
Formal, 6-20 workers	35	0.20	0.39	44	0.45
Formal, 21-75 workers	59	0.34	0.45	73	0.47
Formal, 75-149 workers	23	0.50	0.52	29	0.49
Formal, 150+ workers	19	0.68	0.51	28	0.42
Food, formal	41	0.49	0.60	56	0.54
Wood, formal	39	0.23	0.31	44	0.38
Textiles, formal	34	0.21	0.32	49	0.40
Metals, formal	41	0.41	0.47	47	0.47
All	211	0.26	0.37	266	0.44

As argued above, comparisons across sectors should be interpreted as differences in productivity, not efficiency, because of the possibility that the intercept of the frontier production function may differ across sectors. We may thus conclude that food is the most productive sector, followed by metals. Productivity in food is 40-120% higher, and in metals 20-85% higher, than in wood and textiles, depending on model. These relationships hold when size categories are compared for individual sectors.

5. Determinants of productivity: A discussion

In the previous section, we analysed the variation in technical efficiency and productivity across sectors and categories of firms. A logical second step is then to unveil the underlying causes for these differences. Potential determinants are scrutinised below together with their expected influence on performance. Empirical estimations are conducted in section 6 using average production functions augmented with the determinants. Our analysis therefore focuses on productivity, not technical efficiency, although the arguments presented below relate to both concepts. We prefer this approach to an analysis of the determinants for technical efficiency because it is simpler, does not rely upon the assumption that efficiency is independent of inputs, and that parameter coefficients of all variables are directly interpretable in a straightforward manner. Also, if the background variables of interest for the performance of manufacturers are available a priori, as is the case here, ordinary least squares regression will 'do just fine', as Knox Lovell (1993, p7) puts it.

For natural reasons, the discussion below focuses on firm specific factors rather than factors that are common to all firms. Of course, factors such as corruption, regulations, taxes, infrastructure, overall education levels and cultural attitudes by the workforce, aggregate demand, political instability and institutional efficiency all affect performance of firms to some extent. But the point is that they affect all firms more or less equally, and they do not predict the variation between firms in any foreseeable way. The firm-specific factors we consider are: location, age, growth, investment rate, capacity utilisation, skilled labour ratio, race of owners, whether or not the firm exports, degree of foreign ownership, and access to credit.

The location variable considers the different effect on productivity that may exist between the three categories of towns. Mombasa, the main port of entry, would confer transportation cost advantages on both imported inputs and exports. Nairobi has the advantage of being the capital with all government offices and a more developed infrastructure relative to the smaller cities of Eldoret and Nakuru. Eldoret, the newest and fastest growing industrial town could also enjoy some advantages.

The inclusion of the age and growth variables is motivated by the literature on firm growth. A seminal contribution to this literature is a selection model by

Jovanovic (1982), in which the underlying cause for different growth patterns among firms is the variation in their efficiencies. Profit-maximising output is an increasing function of firm-level efficiency that is fixed. Since the efficiencies are unknown to the managers, they must infer it through operating in the market, a process that takes time because of noise. Over time, efficient firms grow and survive, while inefficient firms remain small or exit. This implies that larger firms are more efficient than small and that growing enterprises are more efficient than contracting ones. Also, older firms, on average and for a given age, are more efficient than younger ones as a result of the selection process taking place. Several variants of this model exist (see, for instance Pakes and Ericsson 1987, and Hopenhayn 1992) but its main results hold. If the Kenyan manufacturing firms conform to this theory, we expect both the age and growth variables to have positive signs. In addition, a positive age variable may also be an effect of learning-by-doing effects, leading to accumulation of experience and improved productivity over time.

The investment rate is ambiguous. If it proxies firm growth, we may expect it to be positive because of the argument above. On the other hand, if adjustment costs of capital investment are present, it can be negative. It is notable that the investment theory literature neither incorporates efficiency nor productivity explicitly in the analysis (Chirinko 1993). The degree of capacity utilisation must have a positive effect on productivity unless the capital stock has reached levels of congestion, which is not likely anywhere in Africa. Human capital is captured in the ratio of skilled labour to the total labour force, and is expected to have a positive effect on productivity. Its relative impact can be regarded as a test of Hamermesh's (1993) claim that the main constraint in many developing countries is skill, not physical capital. The race factor aims to isolate the relative inexperience of the African late starters and hence their relatively shorter duration of learning-by-doing. The Africans' relative lack of access to financial and other related resources work in the same direction.

The export promotion hypothesis postulates that exporting firms are more productive than non-exporters. Productive firms self-select into exporting. The competitive pressure in the export markets can also spur firms to raise their performance. The degree of foreign ownership may have a positive influence if it involves better technical support to the firm, or tighter monitoring of managers to be efficient, had the owners been exclusively Kenyans. If working capital is a main constraint for firms, we may expect access to credit to contribute positively to productivity by relieving the management efforts in the procurement of financial inputs. As informal firms are distinct in terms of low age, no access to formal credit, high degree of African ownership, no export involvement or foreign ownership, inclusion of an informal dummy would lead to severe multicollinearity problems among the explanatory variables in the following analysis. It is therefore omitted.

Naturally, the direction of causality of these determinants is not always obvious. In fact, for some it may go both ways. For example, are firms more productive because they export, have access to credit and have foreign owners, or is it the other way around, so that they possess all these characteristics because they are productive? Or, are both statements true? Clearly, one can certainly argue for either case. However, it is beyond the scope of this paper to settle this issue and we shall therefore regard the estimated relationships in the next section as associations rather than casual links.

The definitions of the determinants are as follows. Firm age (*Age*) is measured in years since operations started. The growth variable (*Growth*) is defined as, $Growth = \Delta L_t / \max(L_{t-1}, L_t)$, which is bounded in the [-1, 1] interval. The investment variable (*Invest*) is total investment in capital goods undertaken during the year divided by capital input.[6] The capacity variable (*Capacity*) is defined as the percentage utilisation rate of the capital stock under current working hours. The skill variable (*Skill*) is defined as the ratio of skilled

[6] Values exceeding 0.5 are considered implausible and therefore set to 0.5. The correction is made for 31 observations.

to the total number of workers.[7] Because of measurement problems associated with this variable for small firms, it is set to zero for establishments with less than ten workers. The *African*- and *Export*-variables are dummies for African ownership and involvement in export markets, respectively. Foreign ownership (*Foreign*) is measured in percentages, and the *Credit*-variable is a dummy variable taking the value of one if the company has access to an overdraft facility at a bank.

Means of these determinants are presented in table 5. In terms of age, capacity and skill, the sectors are notably similar. Considering other variables, some interesting differences emerge. It is intriguing that the growth rates follow the ranking in efficiency levels in section 4, with food at the top, followed by metals. These two sectors are also much more involved in export markets than wood and textiles.

Table 5 Sample means of the nine productivity determinants

	All	Food	Wood	Textiles	Metal
Age	19.86	20.52	20.94	20.18	17.96
Growth	-0.01	0.02	-0.04	-0.05	0.00
Invest	0.08	0.10	0.08	0.05	0.07
Capacity	0.64	0.65	0.68	0.62	0.61
Skill	0.20	0.18	0.22	0.20	0.19
African	0.37	0.29	0.37	0.34	0.48
Export	0.23	0.27	0.16	0.19	0.31
Foreign	9.76	10.26	12.52	6.14	9.73
Credit	0.60	0.75	0.56	0.56	0.54

The bivariate Pearson rank correlations in table 6 display a number of significant associations among the variables. The perhaps-strongest correlation is with firm size (*Size*), measured as the natural logarithm of the number of workers, which is positively related to age, skill, export, foreign ownership and credit. Likewise, export is positively correlated with age, foreign ownership and credit. The growth variable has, surprisingly, the smallest and least significant

[7] Skilled workers include managers, proprietors, engineers, physical scientists, accountants, economists, technicians, foremen, supervisors, and specifically skilled production workers.

coefficients. African ownership is strongly correlated with young age, lack of skill, little export involvement, small degree of foreign ownership, rare access to formal credit and small size. As argued above, these are the characteristics of informal firms, which motivated the exclusion of an informal dummy variable from the productivity analysis below on multicollinearity grounds.

Table 6 Correlation matrix of the productivity determinants.

	Age	*Growth*	*Invest*	*Cap*	*Skill*	*African*	*Export*	*Foreign*	*Credit*
Growth	-0.17*								
Invest	-0.22*	0.16*							
Capacity	0.04	0.09*	0.08*						
Skill	0.24*	-0.06	-0.17*	0.07#					
African	-0.40*	0.04	0.14*	-0.10*	-0.34*				
Export	0.14*	0.04	0.03	0.05	0.19*	-0.27*			
Foreign	0.25*	-0.03	-0.05	0.05	0.08*	-0.27*	0.34*		
Credit	0.33*	-0.09*	-0.15*	0.04	0.39*	-0.50*	0.36*	0.22*	
Size	0.38*	0.00	-0.08*	0.21*	0.42*	-0.55*	0.57*	0.33*	0.65*

NOTE: The * and # symbols signify significance at the 5 and 10% levels.

6. Determinants of productivity: Results

The analysis of the determinants for productivity is conducted using ordinary least-squares regression with output as the dependent variable, and the inputs and determinants as explanatory variables. As with the FE-models above, weights are used in the estimations to correct for heteroscedasticity. For some of the determinants, as discussed above, the direction of causality may go both ways. For this reason, the estimated parameters should be interpreted as the nature of *association*, rather than *causation*, between the determinants and productivity. It follows that the parameter estimates may be subject to the same unknown degree of simultaneity bias as discussed in section 4.

To explore some of the heterogeneity of the sample, we present both pooled and sector models in table 7. The labour elasticities are somewhat higher than estimated with the models in section 4, whereas the capital elasticities are in between those estimated with the FE and RE-models. Constant returns to scale cannot be rejected in any model except in textiles according to the Wald tests reported at the bottom end of the table, which is consistent with our previous analysis. The time variable is insignificantly different from zero in all models, which means that no technical change is picked up in the regressions, except textiles.

Thus, textiles behave rather differently compared to the other sectors as both significant decreasing returns to scale (0.6) and negative technical change (-0.2) is estimated in the sector. Most likely, this is an effect of the dramatic drop in aggregate output of almost 50% in the sector following the sudden inflow of imported used clothes, which occurred in the middle of the sampling period. As a response to this cut-throat competition, many producers were unable to survive the falling prices and began reorient their activities towards alternative areas, such as services. A general impression from the field by the interviewers was that such transformations were a lot easier for small than for large firms. The low estimate for returns to scale may therefore capture such inability of the larger establishments, with specialised production lines and machinery, to change market niche.

The sector dummy variables in the pooled model confirm our earlier findings that food, followed by metal, is the most productive sector. The coefficients suggest that food is approximately 70% more productive than wood and textiles, and 40% more productive than metals, which is roughly consistent with our earlier inter-sectoral comparisons. The Nairobi and Mombasa dummy variables are significantly positive in the pooled model, suggesting that location in the capital or in the main trading port may influence productivity positively. The location influence is positive in all sector models, excluding textiles, but are generally insignificant. Interestingly, textile firms, located especially in Mombasa but also in Nairobi, are significantly less productive than those in the base regions Eldoret and Nakuru. Presumably, the negative consequences of competition discussed above are stronger in places where this competition was most serious. Such a place is certainly Mombasa, the principal port for overseas imports, where no transport costs inflated the price of imported clothes.

The firm age variable is insignificant everywhere except textiles. Hence we find no support for the Roberts and Tybout (1997) argument that productivity increase with firm age until a threshold age of about four years, nor does it support the hypothesised positive age-productivity relationship in the firm growth literature. The textiles exception may be due to older firms also being the larger ones, which were struck particularly hard by the trade liberalisation mentioned above.

The firm growth variable was divided into two separate variables to allow for distinct growth-productivity relationships for expanding and contracting firms. Because of the poor quality of this variable in terms of magnitude[8], but not in sign, we entered firm growth in the regressions as dummy variables. Specifically, we defined the variable *Dgrowth* to takes the value of one for firms with a positive growth rate of three percent or more, and zero otherwise, and the variable *Dcontract* to take the value of one for firms with a negative growth rate exceeding three percent, and zero otherwise. Interestingly, *Dgrowth* is negative and significant in the pooled model, which contradicts our expectations, but not so in the sector models. On the other hand, *Dcontract* is significantly negative both in the pooled, food and metal models, which is consistent with most theories of firm growth, including the Jovanovic model, and with our discussion in the previous section.

The investment ratio is positive and insignificant at the 5%-level in all models. If anything, this is weak evidence for a positive association between productivity and the investment rate. Again, causality can clearly go both ways: probably, as argued in the section 5, is even the reversed direction more likely for this particular variable. In any case, the results in table 7 do not contradict the previous findings, although the size and significance of the parameter estimates should be interpreted with great care.

Capacity enters with the predicted positive sign, and is significant in the pooled and textiles models. The human capital variable does not influence

[8] The growth variable is not based on the input L, but on related data on net hiring during the year because L was not observed for the previous period for half of the observations. The two variables, where observed, differ in size but rarely in sign, which motivates the use of growth dummy variables.

productivity significantly in any sector except food, where the effect is positive and rather strong.

Table 7 Parameter estimates of productivity regressions.

	Pooled Coeff. (s.e.)	Food Coeff. (s.e.)	Wood Coeff. (s.e.)	Textiles Coeff. (s.e.)	Metal Coeff. (s.e.)
Intercept	9.118*	8.772*	9.557*	13.138*	9.077*
	(0.461)	(1.110)	(0.872)	(1.039)	(1.025)
ln(*K*)	0.249*	0.246*	0.196*	0.191*	0.255*
	(0.030)	(0.083)	(0.060)	(0.068)	(0.064)
ln(*L*)	0.733*	0.749*	0.824*	0.422*	0.788*
	(0.051)	(0.134)	(0.104)	(0.114)	(0.103)
t	-0.010	0.030	0.017	-0.228*	0.128
	(0.046)	(0.122)	(0.089)	(0.088)	(0.092)
WOOD	-0.677*				
	(0.120)				
TEXTILES	-0.784*				
	(0.127)				
METAL	-0.435*				
	(0.118)				
NAI	0.494*	0.135	0.630*	-0.480#	0.215
	(0.108)	(0.247)	(0.184)	(0.263)	(0.306)
MOM	0.459*	0.513	0.261	-1.320*	0.448
	(0.142)	(0.357)	(0.309)	(0.300)	(0.354)
ln(*Age*)	-0.039	-0.003	-0.196	-0.372*	-0.265
	(0.065)	(0.165)	(0.130)	(0.122)	(0.183)
Dgrowth	-0.216*	0.085	-0.230	-0.185	-0.281
	(0.100)	(0.262)	(0.214)	(0.197)	(0.188)
Dcontract	-0.234*	-0.500*	-0.099	-0.138	-0.444*
	(0.087)	(0.250)	(0.163)	(0.158)	(0.206)
Investment	0.444	0.144	0.183	0.250	1.111#
	(0.312)	(0.632)	(0.553)	(0.772)	(0.671)
Capacity	0.363*	0.135	0.323	0.857*	0.339
	(0.165)	(0.421)	(0.339)	(0.289)	(0.334)
Skill	0.254	1.223*	-0.032	0.111	-0.203
	(0.162)	(0.522)	(0.280)	(0.270)	(0.421)
African	-0.219*	-0.209	-0.329	-2.334*	-0.262
	(0.109)	(0.246)	(0.217)	(0.351)	(0.265)
Export	0.228*	0.330	0.521*	0.135	-0.156
	(0.103)	(0.248)	(0.223)	(0.202)	(0.209)
Foreign	-0.001	0.001	-0.004#	0.008#	0.004
	(0.001)	(0.004)	(0.002)	(0.004)	(0.003)
Credit	0.503*	0.902*	0.218	-0.044	0.677*
	(0.110)	(0.293)	(0.187)	(0.219)	(0.286)
Obs	602	114	152	127	142
R-square	0.861	0.855	0.854	0.904	0.893
Tests					
White (a)	0.333	0.746	0.549	0.737	0.499
CRS (b)	0.630	0.952	0.820	0.000	0.596

a) White test of heteroscedasticity. The null is homoscedasticity. Probability value reported.

b) Wald test of the linear hypothesis: ln(*L*)+ln(*K*)=1.00. Probability value reported.

The * and # symbols signify significance at the 5 and 10% levels.

Enterprises with African owners appear less productive in all models. The effect is significant in the pooled and textiles models. The *Credit*–variable is positive and significant in all models except wood and textiles, indicating that access to overdraft facilities is important. Indirectly, these two variables confirm our previous finding that informal firms, almost exclusively managed by Africans and usually with no access to overdraft, are less productive than formal firms.

The export variable is positive and significant in the pooled and wood models, but the magnitude and significance is less than expected and does not lend very strong support for the efficiency-arguments of export promotion. The impact of foreign ownership plays a minor role, and takes both negative and positive signs for the various models, but is insignificant at the 5%-level in all estimations.

Taken together, the results presented above have demonstrated a substantial amount of heterogeneity across sectors. A summary of the main findings in this and in the previous sections, and a discussion of their proposed implications for policy makers, follows in the final section below.

7. Conclusions

We have in this paper analysed the performance of the manufacturing sectors in terms of technical efficiency, technical change and productivity. Our basic tool of analysis was the production function, which served as a best-practise frontier in the measurement of efficiency, and as an average response function in the analysis of the determinants of productivity.

It was found that the estimated input elasticities and returns to scale are strongly dependent on methodology. The results from the unrestricted fixed-effects model suggest decreasing returns, whereas the stochastic frontier model and the average production functions propose increasing and constant returns, respectively. We did not try to distinguish among these models, but we note that this finding is consistent with Roberts and Tybout (1997) and supports their claim that correctly measuring scale returns can be difficult with noisy data.

The mean efficiencies varies across models (see table 4), however, the rankings of sectors and firm categories are basically the same for all models.

We found a strong positive size-efficiency relationship. The fixed-effects model with constant returns imposed suggests formal firms in the 75-149-worker category to be about twice as efficient as formal firms in the 1-5-worker interval. There is weak evidence that efficiency is somewhat lower for establishments in the 150+ worker category, indicating the possible presence of an inverted ∪-shaped size-efficiency relationship. Such a relationship is evident, and much clearer, with the labour and capital productivities which peak in the 25-74- and 75-500-worker categories, respectively. When comparing productivity across sectors, it was found that food is 40-120%, and metal 20-85%, more productive than wood and textiles, depending on model.

In all models, textiles behaved differently from the other sectors when estimated individually. Strongly decreasing returns, a negative and significant time trend and negative influence of location in Mombasa separates it from the other sectors. We believe these results are driven by heavy costs of adjustments following the inflow of used clothes in the middle of the sample period in which gross sector output dropped by almost a half. The general observation from the field that larger firms were less able to adjust quickly may contribute to the estimated decreasing returns.

The analysis of the determinants for productivity revealed some heterogeneity among sectors, which makes it precarious to draw general conclusions in some cases. Apart from textiles, the location variables indicate positive impacts on productivity by operating in Mombasa or Nairobi, although this effect is weak and significant only in the pooled model. The age variable fails to explain much of the variation in productivity, as do the dummy variable for growing firms and the investment ratio. However, contracting firms are shown to be less productive in all models, which is consistent with findings from other developing countries in Roberts and Tybout (1997). In line with their reasoning, we may therefore conclude that an increase in the turnover rate of enterprises in Kenyan manufacturing, in which contracting firms exit, may raise overall sector productivity. Naturally, higher turnover also implies lower mean age, but since age has no effect, this does not affect overall sector performance according to our results.

Firms with African owners and limited access to credit are less productive, and because these are the main characteristics of informal firms, it appears as if productivity is lower in the informal sector. The skill variable does not confirm the Hamermesh (1993) claim that skill is the main constraint for production in developing countries: it has a positive impact in food but is insignificant everywhere else. Further, we find weak support for the export penetration hypothesis, that exporting imply higher productivity, and no support for the argument that foreign ownership has an influence.

Based on these findings, we believe that three conclusions relevant for policy can be drawn. The first concerns the dramatic effects imposed on textiles caused by the import liberalisation of cheap used clothes. The possible gains in consumer surplus must be weighted against the heavy adjustment costs incurred by the textiles sector, and we suspect that a more gradual reform might have been warranted. For future trade reform schemes, these experiences deserve to be taken into account. A second conclusion is based on the observation that overall sector productivity may increase with higher enterprise turnover. To encourage such a process, policy need consider measures that stimulate births of new firms, and not generally to support low-productive firms. A third conclusion is that access to credit appears to be of relatively more importance than export involvement and human capital. This suggests that the government should prioritise reforms that improve access to credit by private firms.

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ARE FORMAL AND INFORMAL SMALL FIRMS REALLY DIFFERENT?

Evidence from Kenyan manufacturing[#]

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Abstract: Although informal establishments dominate the small firm-segment in Kenyan manufacturing, there are also formal companies with distinct characteristics. Informal firms are younger, less capital-intensive, almost never run by Asians, pay less skilled wages and no taxes, have poor access to credit and have less educated managers. They invest more often and are less efficient than Asian-managed formal firms, but more efficient than those managed by Africans. This suggests that formality status, independent of size, matter. Also important is how ethnicity affects these differences and the graduation of firms from the informal to the formal sectors.

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1. Introduction

The informal sector is large in most developing economies, and has been growing fast in recent decades in response to rapid urbanisation rates and the limited ability of the formal sector to absorb the influx of job seekers. In 1997 an estimated 64% of the total work force in Kenya outside smallholder agriculture worked within the so-called 'informal sector' (Economic Survey, 1998).[1] The share of informal employment in manufacturing was even higher at 79%. Understanding the dynamics of the informal sector is obviously of outmost importance for development policy.

A key issue is whether informality is just a matter of the size of establishments, as argued by some, or if it implies structural differences between formal and informal enterprises of equal size. The purpose of this paper is to compare the characteristics of formal and informal firms and to see how these may affect the choice of formality status for new firms. We are particularly interested in whether a case can be made for or against informal manufacturing in terms of productivity, which has been debated for years but rarely empirically analysed. We will also analyse how the two firm categories differ in terms of growth and investment patterns.

Evidence on these three topics may contribute to the debate on whether the informal sector is mainly a manifestation of poverty, with no inherent growth potential, or a dynamic response to the regulatory collapse of the state in developing countries.

The following section reviews the debate on the character of the informal sector and its role in economic development. Given the enormous literature on the subject, we restrict the review to recent contributions within the economics discipline. In Kenya, this sector has an indigenous name, the jua kali (Swahili for hot sun), and this is described in Section 3. Econometric analysis of firm-

[1] According to the definition adopted by the Central Bureau of Statistics, an informal firm is one that is not in the books of the Registrar of Companies.

level data is conducted in section 4. A summary of the main empirical findings and a discussion of their implications conclude the paper.

2. The character and role of the informal sector

In his classical article on the dual economy model Lewis (1954) treated the small-scale, traditional sector as a reservoir of surplus labour without growth potential. The sector was seen as a temporary disequilibrium phenomenon, which would disappear once the economy reached the turning point and the modern sector had absorbed the labour surplus. This view was challenged in the early 1970s, when the concept of the "informal sector" was introduced. The influential ILO report on employment in Kenya of 1972 argued that it could provide a basis for employment creation and growth even in the longer term. Since then there has been a lively debate about the informal sector. This has concerned on the one hand the choice of an appropriate definition and on the other hand the character and role of the sector in development.

Normally one or more of three criteria is used to define the informal sector (Morrison 1995). The first one is size, where the concept of informal is restricted to self-employed and micro-enterprises with less than 10-20 employees. The second criterion concerns legal informality, that is informal enterprises are not registered and do not comply with legal obligations concerning safety, taxes, labour laws etc. The third criterion indicates that the firms should have limited physical and human capital per worker. Sometimes the sector is referred to as a low wage sector. The common point of all these attempts at defining the informal sector is of course that there is a dual structure in the economy, with a formal sector and an informal sector. Fontin, Marceau, and Savard (1997) emphasise the three aspects mentioned above and refer to them as scale, evasion, and wage dualism. The criterion used to define the informal sector in this study is basically the second one, that is legal informality, but the firms are also small and have limited capital.

The second debate, on the character and role of the informal sector, is the more important one. John Harris (1990) has suggested a classification of the various views on the sector along two dimensions. First, does the sector have a growth potential or not, and secondly is it autonomous or integrated with the formal sector? Figure 1 illustrates the classification.

		Autonomy	*Integration*
Growth potential	+	Duality	Complementarity
	-	Marginality	Exploitation

Figure 1. Views on the formal - informal sector interrelationships.

For the pessimists, the sector is either marginalized or exploited. For the optimists, it is either dual or complementary to the formal sector. A recent paper by Ranis and Stewart (1999) extends this discussion and presents a model, where the informal sector is considered to be heterogeneous so that firms can be either productive and dynamic or stagnant and traditional. They go on to analyse the factors that determine the growth of the informal sector, which would have to be based on the dynamic segment of the sector. A key factor is the degree of integration with the formal sector. The higher this is, the higher the growth potential. A more rapid growth in the formal sector and a more even distribution of income also increase demand for informal sector products and thus its growth.

The distinction of the informal sector into a progressive dynamic and a stagnant low-income subsector is not new[2] and is perhaps a possible way to reach some consensus regarding its role in economic development. Clearly, few would contest that there exist examples of informal production in developing countries that conforms to each of the four perspectives in figure 1. What is more important is to establish the relative proportions of dynamic and stagnant informal enterprises, to understand the basic mechanisms that determines these proportions, and to identify relevant policies that can spur and incorporate such dynamism into the national economy.

The industrial structure in Africa is dual, with a large number of very small firms and a small number of medium and large-scale firms and very few firms

[2] See Ranis and Stewart (1999, footnote 7), King (1996, Chapter 6) and ILO (1995).

of intermediate size (i.e. usually defined as 10-100 workers). There has been an extensive discussion about "the missing middle". The question is why small firms tend to remain small, at the same time as the aggregate output of small-scale firms is growing rapidly. Fafchamps (1994) provides an interesting discussion of the question why so few small firms grow to become large firms.

In this paper we will take a step further backwards along the transition path of firms. We note that a huge number of small informal firms are started in Kenya, and that hardly any of those end up being large formal firms. It seems reasonable to assume that to become a medium sized or eventually a large firm, an informal firm first has to become a formal small firm. So there are two hurdles to pass. First, from informal to formal small firm and then from small formal to a larger formal firm. We will here focus on why firms chose to become informal and to stay informal.

Fafchamps discusses six sets of factors that explain why firms generally tend to remain small. We will use his categorisation to guide us in our discussion of the issue of informality. We will argue that these factor also explain why entrepreneurs choose informal status at start-up, and why so few of them ever manage to graduate into the formal sector.

First, it could be argued that the existence of informal firms is a short-term disequilibrium phenomenon, but the fact that these firms have grown rapidly in number is evidence against this explanation. Second, it could be argued that in a situation with high transportation costs it may be rational to produce on a small scale. This is true, but it does not necessarily mean that the firm has to be informal. It could be the case, though, that there are market niches for special products, where there are little scale economies or no need for a capital-intensive technology. Informal firms may then produce such simple or distinct goods. A third set of factors relates to the existence of transaction costs, information asymmetries and market failures. Management requirements are more limited in an informal firm. It may find it easier to control labour and have better access to family manpower. Informal firms may even be an easier outlet for private venture capital than formal firms are. They may also be able to recycle and reuse materials, which the formal sector rejects.

Fourthly, there are the factors relating to government policies and regulations. There are labour laws concerning minimum wages, workers safety, working hours etc that need not be adhered to by informal firms. Then there are taxes and fees, which weigh heavily on formal firms, as do urban planning regulations. There may also be economic and financial regulations, for example price controls, licensing of various sorts, as well as laws with regard to property rights that the informal firms can avoid. Fifthly, when there are fluctuations in demand it may be easier for informal firms to adjust given their flexible technologies and hence avoid the costs associated with idle capacity. Sixthly, managerial ability may vary. Large-scale production requires skills that are not present among small firms.

These factors, possibly with the exception of the first and last one, can be interpreted as costs that hit formal and informal, large and small, differently. Thus, one can interpret the choice of formality status as one based on economic considerations, taking into account the costs and benefits of legal status (Loyaza 1997). The costs of formality that we have discussed above are associated with the entry and operation in compliance with all legal requirements. An informal firm avoids all these by staying informal. The costs of informality includes the continuous risk of being detected and punished by the state for not being formal. Also, they cannot enjoy the services provided by the state, most notably including jurisdictional services such as policing, contract enforcement, protection against burglars, and so on.

Changes in these factors are likely to affect the choice of formality status at start-up and the prospects for graduation from the informal to the formal sector. Clearly, they also affect the growth prospects for small formal firms. A central question is which hurdle is the trickiest one to pass. An examination of the structural differences of formal and informal small firms may provide part of that answer. It would at least cast some light on whether one misses any important variation in the data by grouping formal and informal firms together.

Below we provide some background information on small-scale manufacturing firms in Kenya. We then investigate whether the formal-informal distinction of small establishments makes sense.

3. Jua Kali – Kenya

The Kenyan jua kali sector is a mixture of small self-employment efforts and dynamic enterprises covering a wide variety of activities that concentrate mainly in urban areas but are also evident in rural Kenya. It is estimated that the micro and small-scale enterprise (MSE) sector contributed some 13% of GDP in 1994 (Daniels 1999 p 57). A third of the enterprises operate from homes. Elsewhere, the majority of the enterprises is home based, generally employs only one worker and are women owned. In Kenya, MSEs with a single employee are a minority, only a third are home based, and less than half are women owned.[3] On these accounts, the Kenyan micro and small-scale enterprises are maturer than those found in the rest of the continent.

3.1 Characteristics of the Jua Kali Sector

Informal employment has grown at more than twice the rate of formal employment in the recent decade. Some of this employment results from decreased demand for products by rural artisans, which forces the artisans to shift production from rural to urban areas. The sector is also an avenue through which unskilled persons that move from rural to urban areas acquire skills that enable them to survive in a more challenging urban environment. Urban informal employment also results from the limited formal sector employment opportunities and the presence of young graduates from vocational training institutions, whose curriculum is conventional and offers little specialised skills and therefore limited opportunity for penetrating the saturated formal labour

[3] Women account for less than a half of the MSE entrepreneurs, 40% of the sector's employment and dominate commercial and textile activities. Women enterprises also start smaller, use less start-up capital, grow slower, show uniquely different credit use patterns and are more likely to operate from homes (Parker and Torres 1994).

market. The graduates end up picking up apprenticeships in the jua kali sector to develop specific skills necessary for direct employment in the sector.

The sector is also attractive for skilled persons who either lose formal sector jobs or are debutantes into self-employment, taking advantage of the failures of the formal sector to offer some goods and services on competitive terms. But the sector is a second best choice for those unable to find or keep positions in the formal sector. Detailed analysis of the garments sector revealed that while making extensive use of casual workers, the jua kali sector employs skilled workers for direct deployment in production. Most jua kali firms require workers with skills that school leavers do not have, so that the sector is unlikely to solve Kenya's unemployment problem (Ongile and McCormick 1996).

The largest proportion of proprietors is found in the food and service sectors and the largest proportion of apprentices in garages (Aboagye 1986). Studies have shown that the period of apprenticeship in the sector can go on for as long as three years in the vehicle garages. Some of the apprentices successfully seek government trade test certificates for technician, which are handy for both jua kali and modern sector employment.

Aboagye (1986) demonstrated that the average age of the jua kali enterprises is less than six years. This age varies decisively between location and activities, those in Nairobi and Mombasa being relatively younger than those in the smaller towns. This suggests that most jua kali entrepreneurs move toward the larger towns. Metal working firms and vehicle garages are older than others, and the first two years of a jua kali enterprise seem critical for survival. Mortality is greatest within this age. Absence of entry barriers creates severe competition that leads to the demise of the less efficient and poorly managed enterprises. Most of the enterprises are sole proprietorships except a few partnerships in for example garages and metal fabrication.

Earnings by entrepreneurs are highest in the sectors with higher entry costs such as vehicle garages and metal fabricators. Such earnings are also closely correlated with entrepreneur's educational attainments, which are highest for proprietors of garages and metal fabricators (Daniels and Mead 1998).

Jua kali activities concentrate in specific parts of the cities drawn by availability of services and proximity to markets. Some operate from fixed locations and other from variable locations to obviate official harassment. The majority is tenants, a few are landlords, while others are squatters who neither pay nor own the space they use. Informal food processing, woodworking and metal fabricating enterprises typically operate from make shift shades. Local authorities often destroy the structures in order to relocate them. Due to the temporary nature of the premises, infrastructure services such as water and electricity are difficult to supply, limiting the technological choices available to the enterprise.

Most of the output from the jua kali sector satisfies demand for food and other basic needs by the low and middle income rural and urban Kenyans. Prices are lower than for modern sector products, but the quality is also often lower. Nevertheless, some of the high quality furniture sold in the formal sector is supplied by jua kali enterprises providing an important interface between the two sectors. Contracts with jua kali enterprises are often more flexible and customer relationships more personal than in the formal sector.

A significant part of the informal entrepreneurship results from straddling between formal sector jobs and informal activities. It is also the case that some of the informal entrepreneurs initially gathered their skills while working in the formal sector, although skills also flow in the opposite direction. In a few cases, formal retail and wholesale stores contract informal enterprises to make specified products, facilitated through prepayments to the informal workshops for procurement of raw materials. Incidences of extension of supplier credit from formal to informal firms are evident although this is limited to firm with established trading relationships.

3.2 Government policies towards the Jua Kali sector

The assortment of heterogeneous trade, manufacturing, transport and service activities that constitute the informal sector and peculiarities that bind them were first recognised by the East African Royal Commission in the early 1950s. At the time, they were viewed as urban settlements that were important for African commerce and as growth centres that embodied local talent. Twenty year later, an ILO mission synthesised the myriad issues surrounding informal industry and commerce and brought them out for public debate. The mission recommended elimination of official harassment, increased legitimacy, development of informal technology and promotion of linkages between the sector and the rest of the economy.

Subsequently, policy proposals concerning the sector were dominated by the need to address its credit and extension needs of the sector. But it was in the second half of the 1980s that the policy needs of the sector become part of Kenya's political agenda as evidenced by repeated visits by the head of state to areas of Nairobi known for their concentration of informal activities. During such visits, construction of shades, formation of networks, security of tenure of informal premises, sub-contracting and inclusion of informal sector concerns in the country’s industrial policy become part of the policy debate (Kimuyu 1994). Formally, the 1986 sessional paper on economic management and growth paid tribute to the virtues of the sector, including its ability to conserve foreign exchange, create jobs, develop skills and promote local entrepreneurship (Kenya 1986). The paper also underscored the need to improve the sector’s image, which was hitherto poor.

Issues touched on by the sessional paper were picked up by the 1989-93 development plan (Kenya 1989). The government had put together what was referred to as the Centre Project in 1987, which in turn led to the Small Enterprise Development Project of 1989, which was the precursor to a sessional paper on small scale and jua kali enterprises considered a blue print for the future development of the sector.

The general policy orientation towards the informal sector in recent years embraces the overall privatisation and liberalisation thrust of structural adjustment in which the small business sector is encouraged to meet it own needs. The government's role is limited to the creation of an enabling environment through the development of infrastructure, provision of technical information, facilitation of linkages between large and small enterprises, promotion of networking and development of appropriate laws and regulations (McCormick 1999).

4. Are formal and informal small firms really different?

The title question of the paper is here addressed in relation to a sample of small firms in four Kenyan manufacturing sectors. Specifically, we investigate some of the characteristic differences between formal and informal firms suggested by the literature cited above. These include: a short discussion on the definition; ethnicity patterns; factors influencing the choice of formality status at start-up; compliance with regulations; sources of financing; and types of products. Whether observed differences carry over to the relative performances is analysed by examining productivity and technical efficiency, firm growth, and investments.

The data are drawn from the Regional Programme for Enterprise Development (RPED) survey, initiated by the World Bank in the early 1990s, on manufacturing industries in seven Sub-Saharan countries. The surveys comprise informal and formal firms of various sizes and were aimed to find explanations for the sluggish supply response to the structural adjustment programmes implemented in the region. The Kenyan survey was conducted for three consecutive years (1993-95), which lends it a unique dynamic dimension. The unbalanced panel comprises 276 firms in the food, wood, textile and metal industries, which were observed 658 times. Since the data contain firms with up to 4000 workers, our first step in the following subsection is to define a suitable subsample of small firms.

4.1 Definitional aspects

A common definition of small firms is 1-10 workers. However, in order not to lose observations on informals we have set the threshold slightly higher at 12 workers, which defines a subsample comprising of 71 informal and 40 formal firms observed 266 times.[4] We define an informal firm as an establishment that is not in the Registrar of Companies, which is the classification used by the Central Bureau of Statistics (Economic Survey 1998). Hence, our criterion for identification is solely based on registration rather than on one of the other commonly used ones such as employment size or the stock of physical and human capital (Morrison 1995).

The balance of formal and informal establishments in our subsample (40/71) is by no means representative of the population since the survey was strongly stratified, giving much larger weight to formal than to informal units. Based on official statistics, there are about 75 informal firms to every formal one in the 1-5 worker segment, and around 15 in the 6-20 worker category.[5] It thus appears that a definition on informality based on registration identifies almost same the set as one based on firm size. Still, very small formal firms do exist. Out of the 40 formal establishments, 16 had five workers or less.

There exists less overlap in terms of physical capital as shown in Table 1 below. Formal firms are seven to eight times more capital-intensive in our restricted sample. Consequently, capital productivity is six times higher in the informal sector. The owners/managers[6] of formal enterprises are more educated

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[4] The number refers to the mean number of workers per firms during the sample period, rounded down to the nearest integer, and was set in order to include all informal firms except two abnormally large ones.

[5] These approximations, drawn from Bigsten and Kimuyu (1998), are not very precise and vary substantially across sectors. As the distribution of informal firms was not available between the 1-5 and 6-20 worker categories in the population was not available, this was assumed the same as in the sample.

[6] Although not always evident in the data, they are usually the same person. From here on that is assumed, and the acronyms ‘manager’ and ‘owner’ are used interchangeably.

and have more experience at start-up. Most notably, only 5% lack any degree in the formal sector, compared to 46% in the informal sector.

Table 1. Physical and human capital.

Variables	*Firms*	*Formal*	*Informal*
Capital/workers, (median, in thousands of KSh)	109	136	18
Output/capital, (median)	107	1.2	8.0
Owner's highest degree:			
University degree	107	15%	3%
Professional diploma	107	36%	16%
Secondary school certificate	107	44%	35%
Owner's years of experience at start-up	68	11	7

With respect to physical and human capital, we may conclude that formal small firms appear rather distinct compared to their informal competitors. A definition of the informal sector solely based on the number of workers would therefore also comprise a small number of registered firms. Is this mixing-up of definitions of any importance? Should one distinguish between formality and informality in populations of small firms? Are they different? If formal small firms were little different from their informal competitors would the concept of informality become synonymous with small scale. Indeed, this is what several authors have proposed (Little 1987; Peattie 1986). On the other hand, if formal and informal small firms are distinct, the prospects may look very different for these two classes of enterprises. Ignoring the legality dimension may thus level out important variation in the data. The remainder of this section aims to map out some of these differences.

4.2 Ethnicity

In addition to the distinction of formal and informal factors of production, there exists a marked difference between Kenyans of African and of Asian origin. Ethnicity is a politically sensitive issue in Kenyan business and is potentially of great importance in the analysis because these groups have access to distinct sets of supporting networks. Only two informal firms in our sample are run by

Asians, compared to 69 managed by Africans. The 40 formal firms are more equally distributed as can be seen in Table 2.

Table 2. The distribution of formal and informal firms with African and Asian owners.

	Formal	*Informal*	*All*
African	16	69	85
Asian	24	2	26
All	40	71	111

4.3 Start-up

Ethnicity may have an influence on the choice of formality status when the firm is born. Kenyans of Asian origin have often a longer history of urban business activities than Kenyans of African origin. Kinship and community ties among them are commonly held to be tighter and more supportive, and there is weak integration of the Asian and African business spheres. These factors may reduce the barriers for entering the formal sector for the Asians and hence partly explain why so few Asian-managed firms are informal. Other factors relating to the owner's background may of course also play a role. Some of these are presented in Table 3.

Table 3. Owner characteristics influencing the choice of formality status at start-up. The sample is restricted to the 86 firms, which were started by their present owners. We assume that the firm has not changed formality status since start-up.

Variables	*Firms*	*Formal*	*Informal*	*Asian*	*African*
Years in town by owner at start-up	62	13#	8#	15	9
Age of owner at start-up	76	33	29	30	30
Owner's father had manufact. firm	86	22%	21%	42%	18%
Owner's father was a farmer	86	30%	37%	17%	38%

NOTE: *) and #) denote significant difference of means at the 5% and 10%-levels according to the t-test. This test assumes independence of the classes and normal distribution of the variables. Hence, it is not appropriate for dummy variables.

Managers of formal firms were older and had more experience of the city when they started the firm. More surprisingly, there appear to be little formal-informal differences in terms of the father's occupation. Across ethnicity, this difference is much larger: it is much more common for the fathers of Asian managers to have manufacturing background than it is for African managers. Likewise, fathers of the African managers tend to a larger extent to come from farming activities.

To separate the effects of these variations in the data on the formality-informality decision, a simple binary choice model was estimated modelling the choice of formality status (IS=1 for informal, IS=0 for formal firms) as a function of some of the variables in tables 1 and 3. Probit estimates are presented in Table 4.

Table 4. Probit estimates of the choice of formality status at start-up. The dependent variable is given by IS=1 for informal and IS=0 for formal firms. Robust standard errors (S. E.) reported.

	Model parameters		Marginal effects	
Variable	*Coef.*	*S. E.*	*DF/dx*	*S. E*
Constant	-1.27	(0.99)		
Wood sector$	0.50	(0.56)	0.14	(0.15)
Textile sector$	0.07	(0.57)	0.02	(0.17)
Metal sector$	0.50	(0.62)	0.14	(0.15)
African owner$	2.81*	(0.53)	0.825*	(0.065)
Owner has sec. school cert.$	0.54	(0.43)	0.15	(0.11)
Owner holds a prof. degree$	-0.90*	(0.39)	-0.31*	(0.14)
log(start-up age of owner)	-0.029#	(0.017)	-0.0089#	(0.0050)
Owner's father had manufacturing firm$	0.74	(0.58)	0.19	(0.11)
Owner's father was a farmer$	0.22	(0.40)	0.06	(0.12)
No of observations	76			
Log Likelihood	-28.71			
Pseudo R-square	0.37			

NOTE: *) and #) denote significant difference of means at the 5% and 10%-levels.
$ denotes dummy variables for which the marginal effects refers to a discrete change from 0 to 1.

As expected the parameter estimate for the African owner dummy is positive and significant. A discrete change in this dummy from 0 to 1 increases the probability of choosing informal status by a massive 0.825 given the mean of the other explanatory variables. A professional diploma and higher age of the entrepreneur significantly reduces the probability of being informal. All other variables are insignificant. Hence, human capital seems to matter in the decision. A professional degree seems to stimulate the owner to register the enterprise. His age does the same, which could be explained by greater experience, a taste for being official and 'secure', or better relationships with the authorities that may have taken time to establish. These results are robust to alternative specifications.[7]

4.4 Wages and taxes

Once the choice of formality status is made, one would expect the firms to behave and to be treated differently with respect to a number of aspects. This and the two following subsections briefly investigate some of these differences, including variables relating to wages, taxes and finance.

The notion purported in the literature that wages are lower in the informal sector is not univocally supported by the data in Table 5. Unskilled wages are basically the same irrespective of sector and ethnicity of the manager. In contrast, skilled wages are significantly higher in the formal sector. These figures inform us that skill is compensated for in the formal, but not in the informal, sector. This does not square well with the literature reviewed in Section 2. The incidence of tax payments conforms better to the presumed relationships: more than half of the formal companies pay company tax, and almost a third pay value-added tax. A negligible number of informal establishments pay any of these taxes.

Table 5. Wages and taxes.

Variables	*Obs*	*Formal*	*Informal*	*Asian*	*African*
Skilled wage (1000 KSh/year)	153	39#	29#	37	31
Unskilled wage (1000 KSh/year)	134	28	28	29	28
Pays company tax	155	58%	2%	62%	10%
Pays value-added tax	160	28%	3%	39%	5%

NOTE: *) and #), see table 3.

[7] The linear probability (OLS, with and without robust standard errors) and logit models produce qualitatively the same results. Adding some of the other variables in the tables 1 and 3 gives insignificant estimates and does not alter the basic findings presented above.

4.5 Finance

Although benefited from the ability to avoid paying tax, informal producers are less fortunate in terms of the various finance variables in table 6. There are significant formal-informal differences in terms of possession of overdraft facilities, rating credit as the most serious problem, and being trusted by suppliers of intermediate inputs to delay payments. In essence, this picture is consistent with the literature. Similar significant differences are also evident between Asian- and African-managed enterprises, where the problems of the latter category closely resembles those of the informal companies.

Table 6. Financial and credit variables.

Variables	*Obs*	*Formal*	*Informal*	*Asian*	*African*
Has overdraft facility in a bank	260	38%	7%	45%	11%
Rates lack of credit as no 1 problem	263	19%	41%	13%	38%
Owes money to suppliers of inputs	164	39%	12%	48%	15%
Financing of latest major investment:					
- Company retained earnings	101	72%	54%	72%	57%
- Personal savings	101	9%	29%	3%	27%
- Bank loan	101	10%	4%	6%	6%

NOTE: *) and #), see table 3.

The sources of financing for the latest major investment also differs significantly across sectors: formal firms are more often able to utilise retained earnings for these activities, whereas informal firms to a considerable degree must rely on personal savings. This may indicate that the overall earnings of informal firms generally are lower. Also notable is that bank loans is an uncommon source of finance for both formal and informal small firms.

4.6 Productivity

Assuming that formal and informal firms produce more or less the same products[8], it is possible to compare the two sectors in terms of how well they transform inputs into outputs using production function models. Indeed, much

[8] Listings of the most important outputs by firms does not indicate that formal and informal goods are not substitutes. Neither do they suggest that informal firms are more diversified.

of the debate on the informal sector reviewed in section 2 has been on the relative performance of informal production. To contribute empirically to that debate, we present the results of one average response production function models (OLS), and one stochastic frontier production function model (SFA), in Table 7. A common Cobb-Douglas technology with capital and labour is assumed[9], augmented with intercept shifts for the various sectors and survey waves.

Although the capital elasticity is rather low relative to that of labour, constant returns to scale cannot be rejected, which is in accordance to other studies on the RPED data. The central message of the OLS-model, however, is the weakly positive and insignificant estimate of the informal dummy variable together with the much stronger negative and significant impact of the African dummy. The coefficient suggests that the output is less than half in a African-managed firm, which is a suspiciously high effect.

Among the control variables, it is striking that the coefficient for owner's age is negative and significant, indicating a reduction of output with more than 3% per year, whereas firm age has virtually no effect. This suggests that learning is not a major factor for these firms, and that rising age of the manager reduces his ability to maintain productivity. Access to an overdraft facility is associated with significantly higher productivity, but again is the estimate implausibly high, indicating that it may proxy ability or viability of the firm. These results, including the magnitudes of the parameter estimates of overdraft and African ownership, are robust to alternative specifications.[10]

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[9] Intermediate inputs was not included in the production function because of poor accuracy. Omitting this variable still produces the correct input elasticities provided that intermediate inputs is proportional to output, which is a hypothesis we maintain in the OLS and SFA models.

[10] Panel data models are rejected at the 5%-level as shown in the table. Nevertheless, they produce very similar results. Separate models per sectors and years produce approximately the same results, but most coefficients are insignificant and sometimes very unstable. The translog specification of the technology was rejected in all estimations.

Table 7. Parameter estimates of OLS and stochastic frontier production function models. Robust standard errors reported for the OLS-model.

	OLS		SFA	
Variable	*Coefficient.*	*Std error*	*Coefficient*	*Std error*
Constant	13.04*	(0.80)	11.69*	(0.59)
log(Capital)	0.085	(0.061)	0.106*	(0.048)
log(Workers)	0.80*	(0.13)	0.91*	(0.13)
Wood sector	-0.36	(0.27)	-0.60*	(0.28)
Textile sector	-0.51*	(0.25)	-0.40	(0.28)
Metal sector	-0.17	(0.27)	-0.34	(0.28)
Wave 2	-0.12	(0.18)	-0.15	(0.17)
Wave 3	-0.33#	(0.18)	-0.26	(0.17)
Informal sector	-0.04	(0.24)		
African owner	-0.87*	(0.21)		
Overdraft facility	0.44*	(0.20)		
Owner holds a professional degree	0.11	(0.16)		
firm age	0.0090	(0.0060)		
age of owner	-0.0319*	(0.0090)		
Number of firms	91		107	
Number of observations	224		251	
R-square	0.50			
log-likelihood	-325.17		-404.30	
Breusch and Pagan test for random effects (a)	chi2(1) = 2.52 Prob>chi2 = 0.112			
Hausman test of fixed effects (b)	chi2(6) = 10.79 Prob>chi2 = 0.095			
Likelihood ratio test for inefficiency effects (c)			LR-stat(1) = 10.31 Prob>LR-stat = (< 5%)	

(a) This is the Breusch and Pagan multiplier test of the null that the firm-specific errors are zero ($v_i = 0$).
(b) This is the Hausman specification test of the null that the firm-specific errors are uncorrelated with the explanatory variables.
(c) This is the test for the inefficiency effects in the Battese and Coelli (1992) model, which has approximately a mixed chi-square distribution. For critical values, see Kodde and Palm (1986).
*) and #) denote significance at the 5% and 10%-levels.

Table 7 also presents the results of a stochastic frontier model, which is specified as a special case of the model proposed by Battese and Coelli (1992).[11] This model predicts technical efficiencies (TE) for each of the sample

[11] The model estimated is identical to the Battese and Coelli (1992) model with the efficiency time trend parameter, η, and the parameter for the mean of the truncated distribution of the error term, μ, which is associated with technical inefficiency in production, restricted to zero. See the original source and Coelli (1994) for details. The model was estimated using FRONTIER 4.1b.

firms, defined as, TE = exp($-u_i$), where u_i is a non-negative error term associated with *in*efficiency for the *i*'th firm. These predictions belongs to the [0.1]-interval in which the right end corresponds to full technical efficiency (TE = 1.0).

With respect to the common variables, the SFA model reports parameter estimates similar to the OLS model. The predicted firm-level technical efficiencies are summarised in Table 8, which gives the same general picture as above: Productivity and efficiency vary mainly with ethnicity, and not with formality status. African-managed formal units perform worse than not only Asian-managed formal companies, but also relative to informal enterprises. The relative differences, however, are much more plausible.

Table 8. Mean predicted technical efficiencies.

	Formal	*Informal*	*All*
African	**0.43**	**0.50**	**0.49**
Asian	**0.61**	**0.50**	**0.60**
All	**0.54**	**0.50**	**0.52**

The relationship is further illustrated in Figure 5. The informal enterprises display a large variation in efficiency, whereas the Asian-managed formal firms tend to be located further to the north compared to the African ones. However, all categories of establishments overlap each other.

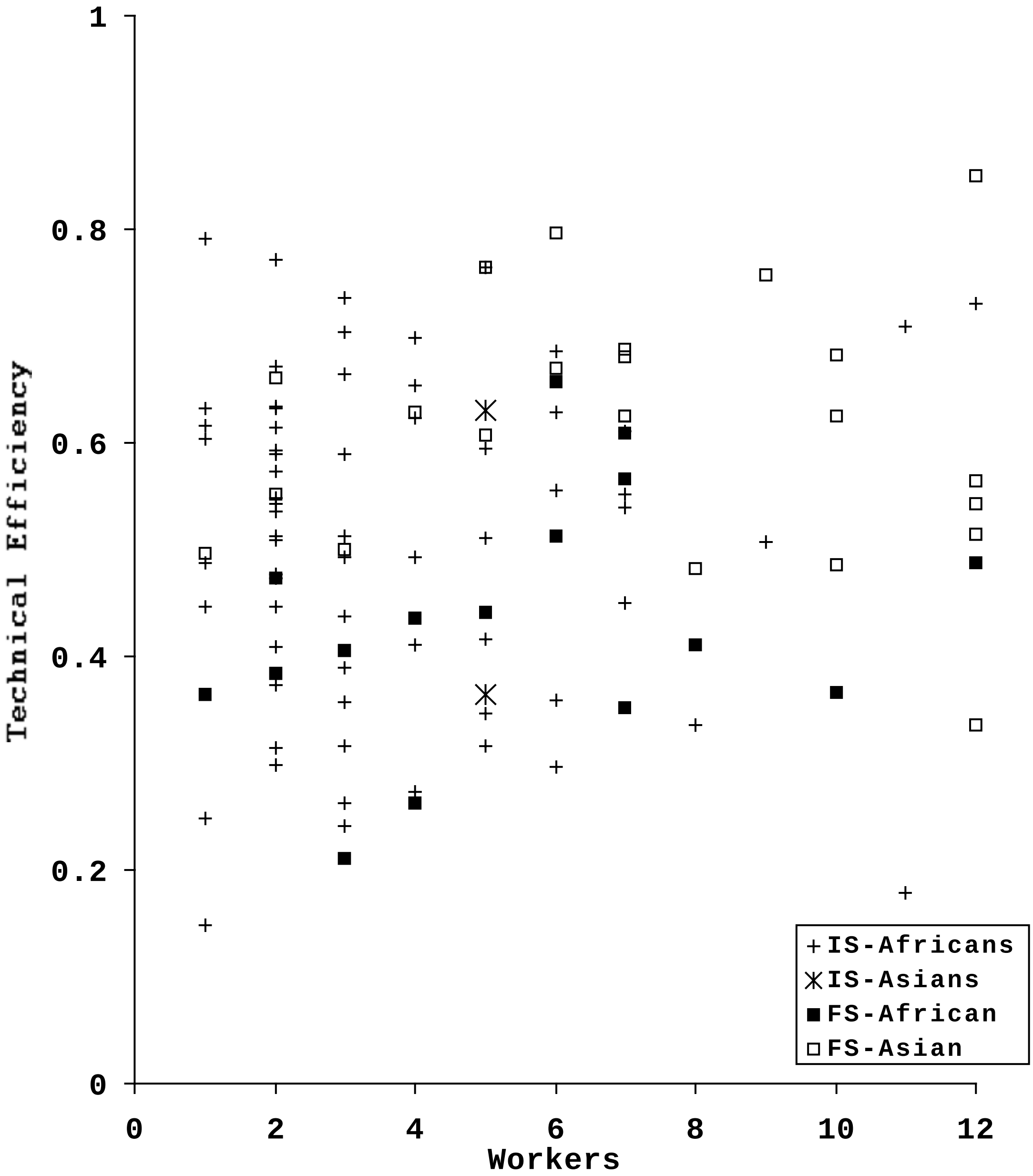

Figure 5. Predicted technical efficiency and firm size.

4.7 Firm growth and investment

Do differences in productivity and technical efficiency affect growth rates of firms? The widely cited Jovanovic (1982) model assumes this implicitly. The model predicts that firm growth is a decreasing function of size and age, and this has gained empirical support (MacPherson 1997), and that efficient firms grow over time and therefore are comparably large, while less efficient stay small or exit, which has received some empirical backing in Kenyan and Ethiopian manufacturing industries (Lundvall and Battese 1998; Mengistae 1996).

If the efficiency-growth relationship is positive, growth would follow the patterns set by the productivity and efficiency estimates above. Table 9 only partly supports this claim. Informal firms exhibit higher growth rates both in terms of workers and output than formal ones. The incidence of informal investment is also higher at 52% vs. 34% for the formal category[12], as is the investment to capital rates. Nevertheless, the investment to output ratios appear similar.

Table 9. Firm growth and investment variables.

Variables	*Obs*	*Formal*	*Informal*	*Asian*	*African*
Yearly growth rate, workers (mean)	245	-0.017	0.067	0.020	0.039
-"- only formal firms	95			0.010	-0.049
Yearly growth rate, output (mean)	133	-0.263	0.026	-0.292	-0.024
-"- only formal firms	49			-0.331	-0.186
Firm age	236	24	11	29	12
-"- only formal firms	92			31	16
Capital/Workers, (median in 1,000 Ksh)	261	125	15	151	22
-"- only formal firms	168			154	86
Proportion of firms investing	253	34%	52%	35%	48%
-"- only formal firms	96			32%	37%
Investment/Capital (median)	114	0.051	0.229	0.030	0.195
-"- only formal firms	33			0.027	0.084
Investment/Output (median)	111	0.040	0.039	0.033	0.040
-"- only formal firms	32			0.034	0.064

NOTE: Firm growth is defined as $\log(X_t/X_{t-1})$ where X denotes workers or output and the time span between t and $t-1$ is one year. Investment ratios (I/K and I/Y) are only computed for investing firms.

Turning to ethnic patterns, we again discover significant differences. African-managed formal companies display negative labour and output growth rates, but despite that they invest more often and at higher rates than Asian establishments. Together with the evidence from the previous section, this may

[12] It is not generally true that informal firms invest more often than formal ones because there exists also a strong positive size-investment relationship. See Söderbom (1998) for details.

indicate that African-owned enterprises during the survey years were involved in substitution of capital for labour, a process that incurred some costs in terms of forgone output and thereby lowered productivity and efficiency.

These findings hold when analysed for separate years, with the exception of the last year of the survey. Nevertheless, other factors than ethnicity and formality status may lie behind these relationships, including firm age, size and other variables. In order to control for these, a model of firm growth was estimated. The dependent variable was defined as in Table 9, i.e. growth = $\log(L_t/L_{t-1})$, where L and t denote the number of workers and the measurement period, respectively. The number of workers is also included on the right-hand side as a explanatory variable, but in order to avoid spurious correlation, this variable was entered with a lag of one year, as suggested by Teal (1998) and Parker (1996).

The results are reported in Table 10. Model 2 is the same as model 1 except for the inclusion of squares and interactions of size and age, and three additional control variables. Both models neutralise the tentative conclusion from Table 9 that informality by itself would be associated with higher growth rates. Instead, this relationship is only a function of firm size, which, in accordance with the literature, is negative. The African dummy exhibits a weak tendency of being negatively associated with growth in Model 1, but this effect disappears as more variables are included in Model 2. All other variables appear insignificant, both individually and jointly, as indicated in the table.

Some caution is appropriate in the interpretation of these results given that the firms that dropped out from the survey between the years are ignored in the analysis. Nevertheless, these dropout rates are approximately the same for each of the four categories of firms.[13] Unfortunately, we do not have a complete picture of which firms that closed, moved or were acquired by other enterprises. If all informal firms that left the sample died, while all the formal firms simply shifted to another location, our informal growth estimates are biased upwards.

[13] 22 firms dropped out in waves 2 and 3, including 7 formal and 15 informal, or, 6 Asian- and 16 African-managed.

However, we would argue that there is no a priori reason to believe that is so. Although the literature suggests higher death rates among informal firms, they also change location more often. Hence, given that the firm has dropped out, there is no immediate reason to suspect that the probability of default is higher for informal compared to formal firms.

Table 10. Ordinary least squares parameter estimates of firm growth model. The dependent variable is defined as $\log(L_t/L_{t-1})$. Robust standard errors.

		Model 1		Model 2	
Variable	*(parameter label)*	*Coefficient*	*Std error*	*Coefficient*	*Std error*
Constant		0.76*	(0.17)	1.00	(0.69)
$\log(L_{t-1})$		-0.296*	(0.047)	-0.44*	(0.17)
$[\log(L_{t-1})]^2$	(size2)			0.032	(0.054)
log(firm age)		-0.049	(0.038)	-0.05	(0.18)
$[\log(\text{firm age})]^2$	(age2)			-0.004	(0.038)
$[\log(L_{t-1})]\times[\log(\text{firm age})]$	(sa)			0.009	(0.055)
Wood sector		-0.135	(0.086)	-0.153	(0.097)
Textile sector		-0.142#	(0.084)	-0.193*	(0.092)
Metal sector		-0.115	(0.099)	-0.15	(0.11)
Wave 2		0.135*	(0.068)	0.135*	(0.068)
Wave 3		0.031	(0.066)	0.075	(0.069)
Informal sector	(is)	-0.059	(0.086)	-0.08	(0.12)
African owner	(afr)	-0.132#	(0.076)	-0.096	(0.092)
Overdraft facility	(cred)			0.088	(0.074)
Owner has prof degree	(edp)			-0.014	(0.087)
log (age of owner)	(age)			-0.03	(0.16)
Number of firms		96		93	
Number of observations		228		217	
R-square		0.21		0.24	
Wald tests:					
H_0: is = afr = 0		F(2,218) = 2.69 Prob > F = 0.07		F(2,201) = 1.56 Prob > F = 0.21	
H_0: cred = edp = age = 0				F(3,201) = 0.50 Prob > F = 0.69	
H_0: size2 = age2 = sa = 0				F(3,201) = 0.16 Prob > F = 0.93	

*) and #) denote significance at the 5% and 10%-levels.

5. Conclusion

The answer to our title question is, “Yes”, informal and formal small firms *are* different. Although the small firm segment is dominated by informal enterprises, formal units of very small size exist, and their characteristics and the environment they operate in are not the same. Compared to formal companies, informal firms are almost never owned by Kenyans of Asian origin, they are younger, pay no taxes, pay less skilled wages (but the same unskilled wages), are less capital-intensive, live under more restricted financial conditions and have less educated managers. These findings are basically those you would expect from reading the literature. More surprising is that informal investment and growth rates are higher. However, the higher growth rates were shown to be entirely explained by their smaller size, and not by informality by itself. Informal firms are less efficient than Asian managed formal firms, but more efficient than those managed by Africans. This suggests some viability and potential of the informal organisation of production.

African-managed formal firms contract in terms of employment, but exhibit positive and higher investment rates than their Asian-managed formal competitors. This indicates that these firms are substituting capital for labour. One of the reasons behind their lower efficiency could be the adjustment costs such a process would incur. It is a very interesting question whether these firms recently graduated from the informal sector, which clearly is an important area for future research. Such research must also consider alternative explanations for these efficiency discrepancies, particularly including the distinct supporting networks the two ethnic groups have access to.

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