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Promoting the Strong or Supporting the Weak? Technological Gaps and Segmented Labour Markets in Sub-Sahara African Industry

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JEL classification: O14 Economic Development, Industrialisation, Choice of technology;

Abstract

This paper analyses intra-industry technological gaps in Sub-Saharan African industry and it inquires into the prospects for technological upgrading. It examines whether and how factor market segmentation (in particular the labour market) and firm specific technological factors are associated with technological gaps. The empirical analysis, based on a sample of industrial enterprises in Ghana and Kenya, shows that it is possible to define technological thresholds, characterised by very significant shifts in technology, initial endowments of technological capabilities and factor market segments. However, if firms have different initial endowments of technological capabilities, they may endogenously choose different technologies and different labour market segments, even when they face the same cost of labour and no other barriers to entry. The paper shows that price denominated policies are insufficient and that policy action should also be directly targeted to easing the process of technological development. The dualistic structure of industry, however, may generate a drawback effect, whereby the overall technological upgrading may cause an increase in unemployment, at least in the short term. Policy makers are therefore confronted by a *promoting the strong vs. supporting the weak* dilemma.

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1. Introduction

The fairly extensive literature on Sub Saharan African enterprises provides incontrovertible evidence of duality and a remarkably low rate of graduation from small-scale low productivity activities to those involving larger scale and modern technologies[1].

Large numbers of firms with less than five employees survive, in the same industry, along with medium-large firms mostly under foreign or state ownership. While the number of indigenous enterprises has increased rapidly in the 1980s, especially in response to recession, the rate of graduation of firms into larger size has been very low in most African countries. The dynamism of African enterprises in other ways, such as the deepening of local linkages, productivity increase, product or technology diversification and export performance has also been low in relation to other industrialising areas. There are few signs that the duality in the industrial structure has been reduced by the modernisation of the traditional sector or by diffusion of technology from large to small enterprises.

Intra-industry technological gaps[2] are often explained in terms of segmentation and imperfections of factor markets other than the market for technology. For example, small firms use different technologies from large ones because they face a higher cost of capital (they have no access to formal financial markets) and a lower labour cost (they can escape labour regulation) and in equilibrium they will choose more labour intensive technologies than large firms. Differences in earnings between workers with the same education in small and large firms are well documented by the literature[3]. More than a decade of structural adjustment, though, shows that price denominated policies are not enough to foster industrial dynamism (Pack 1993). Consequently, there are growing arguments against adopting a strictly price focused approach.

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[1] Kilby 1988, Liedholm 1992, Liedholm and Mead, 1988, Lall 1987b, Lall, Barba Navaretti, Teitel and Wignaraja, 1994, Levy, 1990, Pack, 1993, Page, 1979, Steel and Evans 1984, World Bank, 1989.

[2]. Technological gaps refer to differences in the type of technology used (e.g. hand looms vs. mechanical looms) which, in turn, reflect in differences in capital/labour ratios

[3]. For an overview see Rosenzweig, 1988. For a very recent assessment of wage gaps in Ghana see Jones and Teal, 1994

An important set of arguments revolves around the definition of technology. This can be expanded beyond mere equipment to include other, less tangible attributes, like technological capabilities, i.e. 'the skills, technical knowledge and organisational coherence required to utilise a given technology efficiently' (Lall 1992). Technological capabilities are a unique mix of different inputs combined together by an institution like a firm to function as an organisation (Lall 1992). They are many, more or less complex and they cannot be readily available on the market. If this more comprehensive definition of technology is adopted, technological gaps can be explained by the nature of the process of technological upgrading itself.[4]. Firms may have very different initial endowments of technological capabilities, which may cause persisting technological gaps. The very markets for technological inputs are easily characterised by imperfections and failures, which may affect individual firms in different ways. Internalised transactions, to make up for missing or imperfect markets, may deliver different outcomes in different firms.

This paper is particularly concerned with differences in initial conditions. It shows that if differences in initial endowments of technological capabilities generate persisting technological gaps, then firms may endogenously choose different labour and other (factors) market segments, even when they face the same cost of labour and no other barriers to entry. This framework, which somehow reverts the standard causal link (differences in initial conditions constrain the access to factor market segments and thus the choice of technology), allows us to explain the persistence of the technological gap to changes in factor prices.

This result is supported by the empirical analysis, based on a sample of firms in Ghana and Kenya[5]. It is possible to define clusters of firms characterised by similar technological features (physical and human capital intensity). These clusters are significantly explained by differences in initial endowments (education and ethnic origin of the entrepreneur, foreign and state ownership). In turn, technological clusters are significant determinants of factor market segments (labour, capital equipment and finance).

Policy implications are quite clear: price denominated policies are insufficient and policy action should also be directly targeted to easing the process of technological

[4] Dosi, 1988. Barba Navaretti, 1994c

[5]. The survey was carried out in 1992/93 within the Sub-Saharan African World Bank Regional Programme on Enterprise Development'. It covers four industries: metal working, wood working, food processing and textile and clothing and 150 to 200 firms per country.

development[6]. The dualistic structure of industry, however, may generate a drawback effect, whereby the overall technological upgrading may cause an increase in unemployment, at least in the short term. Policy makers are therefore confronted by a *promoting the strong vs. supporting the weak* dilemma.

The next section develops a theoretical model for a vertically differentiated industry. In section three, firms in the Ghana and Kenya samples are grouped according to their main technological characteristics. Subsequently, technological threshold are defined, whereby technological clusters are associated with shifts in initial endowments (like the education of the entrepreneur) and factor market segments (labour, finance and capital equipment). Section four discusses policy implications and section five concludes.

2. The theoretical framework

This section develops a theoretical framework which embodies some of the key features of the process of investing in technology and technological capabilities. In particular, we want to understand the choice of technology made by firms, which have a history of technological development when they take the investment decision analysed by the model. What happens then? Is the technological advantage self reinforcing, or will the gap be closed in subsequent technological choices? Furthermore, if firms face no constraints or a dualistic price structure in other factor markets (we focus on the labour market), will they endogenously choose different segments of that factor market, i.e. different pools of workers?

The literature on technological development emphasises that technology and technological capabilities are in fact *firm specific*. Besides for differences in initial endowments, firm specificity may emerge because (i) given the very large number of technological inputs, possible input combinations are infinite and may differ from firm to firm (Dosi, 1988, Lall, 1992) (ii) the large number of technological inputs increases the possibility of market failures in any individual input market, (iii) in-house technological inputs are developed inside the firm and they are heavily characterised by the nature of the learning processes (learning by doing and learning to learn) (Stiglitz, 1987), by a high degree of uncertainty, by market failures typically affecting internalised transactions, (iv) technological

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6. Pack, 1993

knowledge may be to a large extent tacit, i.e. not codified in an easily transmissible form (David, 1992).

To make things simpler we examine the case of a duopoly (the model can easily be extended to an oligopoly) for a vertically differentiated industry, i.e. product quality differs across firms. In this case, the outcome of the investment in technology is a higher level of product quality[7].

All consumers in the market have the same utility function:

$$U = (qx)^{\beta} y^{(1-\beta)} \qquad \text{for } 0<\beta<1$$

where x is the differentiated good of the industry we are analysing, q the quality of x and y an outside composite goods. Each consumer k will spend the share ß of its income z_k on good x and the remaining on good y, independently of prices and quality level.

Total expenditure for good x in the market is:

$$S = \Sigma_i p_i x_i = \Sigma_k \beta z_k$$

for i= 1,2 denoting the two firms and k = 1,..m denoting the k consumer in the market, and m is the total number of consumers in the economy.

The problem of the consumer k is to maximise utility subject to:

$$\Sigma_i p_i x_{ik} = \beta z_k$$

In equilibrium, this corresponds to choosing the variety with the highest quality price ratio. Therefore, if both firms sell in the market, the following condition must hold:

$$q_1/p_1 = q_2/p_2 \qquad (2.1)$$

---

7. This model is partly derived from models developed by Shaked and Sutton 1983, 1984 and Sutton,1991. For an application to the delocalisation decision see Motta 1992. For an application to the textile industry, see Barba Navaretti, 1994a.

i.e. the quality price ratio must be the same for both firms.

If 2.1. holds, each consumer is indifferent between buying good 1 or 2. This implies that there is no relationship between the income of the consumers and the level of quality they choose and that the market for product x is not segmented. Average variable cost c is constant and it is the same for both firms. Investments in technology have an impact on product quality and not on variable costs. Firms have to bear a sunk cost in order to acquire a given level of technology. Here, it is assumed that the sunk cost raises with the level of quality q:

$$F(q)_i = \alpha_i q_i^2 \qquad q \geq 1 \quad \text{and} \quad \alpha_i \geq 1 \qquad (2.2)$$

There are increasing marginal costs in investing in technology[8]

Coefficient α_i is a declining function of the technological advantage of firm i, γ_i and we can define it as the cost of quality coefficient:

$$\alpha_i = f(\gamma_i) \qquad \text{with} \qquad \delta\alpha_i/\delta\gamma_i < 0$$

The higher the technological advantage of firm i, the lower α_i and therefore the smaller the investment to achieve any quality level q_i. γ_i is exogenous.

We assume that the labour market is the only factor market facing the two firms (besides those factors acquired through the fixed investment in technology and thus quality). There are two pools of workers educated and uneducated. All firms have unconstrained access to any market segment and all firms face the same factor cost in each segment. There is not a dualistic structure of earnings in the most common sense, whereby firms of different size face a different direct cost for labour of the same observable quality. The choice of the market segment is therefore endogenous. The two pools are characterised by

8. This assumption corresponds to the standard assumption of diminishing returns to R&D expenditure. This assumption does no longer hold if we assume that there is a cumulativeness in the investment in quality, i.e. the higher the quality level, the cheaper to increase quality further (see Stiglitz 1987 and Dosi, 1988), which in certain cases can be true. For example, when there is asymmetry of information and quality is not fully perceived by the consumers, it can be shown that only high quality firms will find it convenient to advertise in order to build up a reputation (see Rodrik, 1988).

institutional asymmetries as far as hiring and training procedures are concerned. Educated workers are trained in vocational training schools. Uneducated workers are trained by their masters through an apprenticeship programme. The former must be hired through official channels (e.g. the labour office) and officially registered as employee. The latter can be hired through informal channels and they do not need to be officially registered. The cost of the educated workers (salary and other benefits) is higher, therefore:

$$c_{ie} > c_{iu}$$

where c_{ie} is the variable cost when firm i hires workers with vocational training and c_{iu} when it hires workers without vocational training. Thus, variable costs differ because of education and labour market regulation.

Firms can either choose uneducated or educated workers, but cannot have a blend of the two. The type of workers chosen affects the relationship between α_i and γ_i , i.e. the cost of achieving a given level of quality varies depending upon the type of workers. We assume the following:

With uneducated workers:

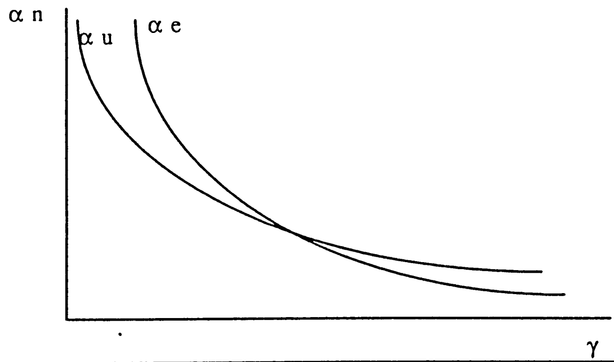
$$\alpha_{iu} = a(\gamma_i)^{-1} \qquad (2.3a)$$

and with educated workers:

$$\alpha_{ie} = b(\gamma_i)^{-2} \qquad (2.3b)$$

The shapes of the two functions are shown in figure 1:

Figure 1
Technological advantage and cost of quality coefficient



The cost of quality coefficient declines with the technological advantage γ, independently from the type of workers selected. For low levels of γ, α is lower with uneducated workers. This is because of mismatching between the type of skills learned at school and those required in the firm and between workers expectations and opportunities in poor technology firms. When γ increases, though, α declines more steeply with educated workers: educated workers are more able and prone to exploit the technological advantage of the firm. Therefore, the two curves cross and beyond a given γ, α is lower for educated workers.

Given our assumptions, the profit function of firm i is:

$$\Pi_i = (p_i - c_n)x_i - \alpha_{in}q^2_i \qquad (2.4)$$

for n = e,u .

Now, we are able to compute the equilibrium. The model is analysed as a three-stage game. In the first stage, firms choose their favourite factor market. In the second stage, firms decide their optimal quality level and in the third stage they play a Cournot game and decide the quantity produced in equilibrium.

The model will be solved by using the backward technique, i.e. by computing sub-game perfect Nash equilibria: first, the Cournot-Nash equilibrium quantities are found, given quality; second, qualities are chosen, (under the assumption that players have perfect foresight on the effects that quality have on profits in the next stage of the game). Finally, the choice of the market segment is made (under the assumption that players correctly anticipate the outcome of the two subsequent stages of the game - quantities and qualities).

Hence, we first compute *the Cournot-Nash equilibrium* (for notational simplicity we omit the subscript n at this stage). Given (2.1) and total expenditure on good x, prices can be re-written as:

$P_i = Sq_i/(q_i x_i + q_j x_j)$ for $i = j$ (2.5)

If we replace the new definition of prices into the profit functions (2.4) and we differentiate them with respect to output, we obtain equilibrium outputs for given qualities:

$x_i = Sc_j q_i q_j/(c_j q_i + c_i q_j)^2$ (2.6)

By substituting (2.6) into (2.5) we obtain *prices and profits* corresponding to the Cournot equilibrium[9]:

$P_i = c_i + c_j(q_i/q_j)$ (2.7)
$\Pi_i = S(c_j q_i)^2/(c_j q_i + c_i q_j)^2$ (2.8)

We can now look for the solution of the *quality game*. Firm i will chose its level of quality q_i by maximising:

$\Pi_i = S(c_j q_i)^2/(c_j q_i + c_i q_j)^2 - \alpha_i q^2{}_i$ (2.9)

given q_j. In other words, it chooses quality having perfect foresight of the solution of the quantity game.

Equilibrium quality is given by:

$q_i = \alpha_j(Sc_j/c_i)^{1/2}/[\alpha_j(c_j/c_i)+\alpha_i(c_i/c_j)]^{3/2}$ (2.10)

9. Second order conditions are also satisfied.

Second order conditions are also satisfied.

The following *conclusions* can be drawn from (2.10). *First*, quality of firm i will be higher the smaller i's cost of quality coefficient with respect to j's and the larger the size of the market S. *Second*, if the firm specific advantage differs, i.e. α_j is different from α_i, firms will choose different level of investment in technology, even when firms employ people from the same market segment, i.e. when $c_i = c_j$. The firm with a lower technological advantage will be trapped in a poor technology equilibrium[10]. If we assume that i is the high technology firm and j the poor technology firm, the technology gap is given by:

$$v = qj/qi = (\alpha_i/\alpha_j)(c_i/c_j) \qquad (2.11)$$

Third, the level of the investment in technology depends on the nature of the competition between firms. Firms engage in a quality race and the higher i's quality the higher will be j's quality (and therefore the investment in technological capabilities). From (2.8) we can also see that the higher i's quality the lower j's profits and vice versa. In fact, condition (2.7) shows that the equilibrium price quality ratio increases with quality \[11]. Therefore i, for any qi must set a lower price in order to match condition (2.1.)

We now move on to examine the choice of the labour market segment. In order to do so, we need to substitute equilibrium qualities (2.10) into the profit functions (2.9). After some calculation we obtain the following profit functions in terms of c and α:

$$\Pi_i = S(\alpha_{jn})^3(c_{jn})^6/[(c_{jn})^2\alpha_{jn} + (c_{in})^2\alpha_{in}]^3 \qquad (2.12)$$

(2.12) represents profits functions when the two firms use different types of workers and therefore marginal costs differ. When they hire the same type of workers, and therefore they have the same marginal costs, (2.12) can be rewritten as:

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10. This result would not necessary occur if both firms have a low γ and they choose a different market segment, so that $\alpha_{ie}<\alpha_{ju}$. However, we will see that the equilibrium conditions ruling the choice of the market segment ensures that this case never arises.

11. This is easy to prove. From condition (2.7) we have that:

$$\delta pj/\delta qj = 1/qi.$$

As qi > 1 by hypothesis, in equilibrium pj increases less then proportionally than qj

$$\Pi_i = S(\alpha_{jn})^3/[(\alpha_{jn} + \alpha_{in}]^3 \quad (2.13)$$

Now, by comparing profit functions of i and j when they use educated or uneducated workers, we can show that:

$$\Pi_i(n_j,u_i) > \Pi_i(n_j,e_i)$$

whenever

$$\alpha_{iu}/\alpha_{ie} < (c_e/c_u)^2 \quad (2.14)$$

i.e. whatever the choice of j, firm i profits with uneducated workers are higher than with educated workers when 2.14 is met.

Condition (2.14) shows that each firm (i or j) will choose the labour market segment (a) only on the basis of its own cost parameters and (b) independently of the strategy chosen by the other firm.

In other words, firm i (j) will choose unskilled workers only when the increase in the cost of quality is more than compensated by the decline in variable costs, due to the fact that unskilled labour is cheaper.

This condition can be characterised more clearly if we substitute (2.3a) and (2.3b) into(2.14) and we derive the γ^*, the level of technological advantage for which firm i is indifferent between hiring educated or uneducated workers:

$$\gamma^* = (c_e/c_u)^2(b/a) \qquad (2.15)$$

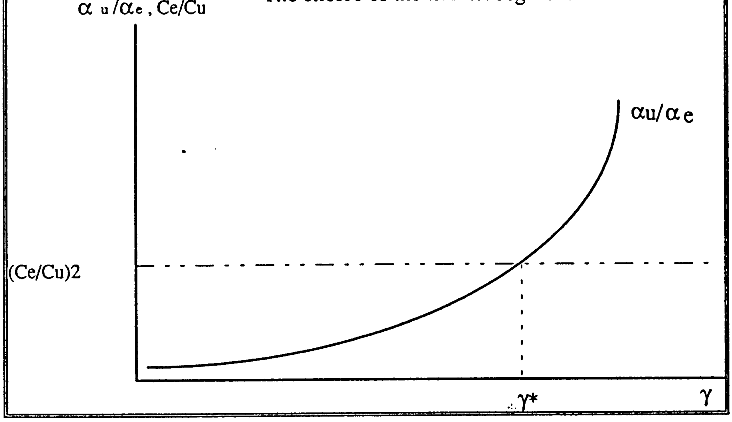
Given that the RHS is constant and the same for both firms, (2.15) implies that firms with a technological advantage higher than γ^* will choose educated workers, and uneducated workers otherwise. Therefore, (i) the firm with a higher technological advantage is more likely to choose educated workers and (ii) the two firms will choose a different market segment, i.e. market segmentation emerges as an equilibrium solution, if:

$\gamma_j < \gamma^* < \gamma_i$,

This result can be shown easily with the help of Figure 2. Curve α_u/α_e, represents for firm i,j the values of the ratio α_u/α_e corresponding to different values of γ and it is increasing in γ. At γ^* the curve α_u/α_e crosses the straight line $(c_e/c_u)^2$.

Figure 2

The choice of the market segment



Note that the indifference level of the technological advantage will be higher the higher the relative cost (i.e. the higher c_e/c_u) and the lower the relative quality efficiency (i.e. the higher b/a) of educated workers.

We have therefore shown that (i) differences in initial technological conditions cause persisting technological gaps within the same industry; (ii) this process is independent of distortions in factor markets; (iii) factor market segmentation may emerge endogenously, following the choice of the technology.

3. Technological Gaps: Evidence and Determinants

This section will test a set of hypothesis about the nature and the determinants of technological segmentation. *First,* whether there are firms with different levels of technological complexity within the same industry. *Second,* whether differences in technology are continuous or discrete. If the latter holds, we expect to find discrete clusters grouping firms with similar technological features. *Third*, whether technological clusters can be associated with differences in initial endowments and/or segmentation in the labour and other factor markets. More specifically, whether it is possible to define technological thresholds, where changes in technology are associated with significant shifts of initial endowments and market segments. *Fourth*, whether initial endowments are significant determinants of the technological clusters. *Fifth*, whether technological clusters are significant determinants of factor market segments.

The analysis is based on the evidence gathered in 1992/93 for two samples of industrial enterprises in Ghana and Kenya[12]. The firms belong to four industries, food processing, textile and clothing, metal working and wood working. The survey, probably the largest and the most detailed available for industrial enterprises in Sub-Saharan Africa, was carried out by the Africa Technical Department of the World Bank, for the Regional Programme on Enterprise Development.

The data set allows us to 'map out' the production structure and the human capital of the firms in the samples. Although they do not measure technological capabilities in a broad sense[13], equipment and human capital are good proxies of the technological complexity of the firm. Technological capabilities are equipment specific[14], i.e. they are expected to increase with the complexity of the equipment. Equally, the more complex the technological capabilities necessary to perform technological functions in the firm, the higher the human capital requirement[15].

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[12] The sample is composed of 157 firms for Ghana and 193 firms for Kenya. The initial sample was larger, but some observations had to be deleted because of missing values and/or outliers

[13] For a detailed classification of technological capabilities, see Lall, 1987a

[14]. See Atkinson and Stiglitz 1985 and Stiglitz 1987 for a discussion about how far technological capabilities are technology specific.

[15]. For an assessment of the relationship between the data collected in the surveys and broader indicators of technological capabilities see Lall, Barba Navaretti, Teitel and Wignaraja, 1994 and Barba Navaretti 1994b

3.1. Mapping out technology: principal components and clusters

The *clustering technique* is probably the most useful statistical tool to analyse if differences in groups of firms characteristics (like indicators of physical and human capital intensities) are characterised by discrete jumps. The technique groups firms according to the degree of vicinity of a selected set of variables. If such clusters emerge, with significant differences between the groups in the variables taken together, the hypothesis that there are discrete changes in technology is supported.

In order to form the clusters we used three sets of variables, listed in table 1, measuring size (number of employees and sales), technology (capital intensity and labour productivity), human capital (education of the managers, of the production workers and of the technical personnel).

The first set of variables was introduced to assess the hypothesis that human and physical capital intensity increase with size. This is the case when there are increasing returns to scale in investing in technology. The extent at which scale matters will depend on the type of technological capabilities, on the nature of the equipment, on the existence of learning by doing processes and on whether increasing internal division of labour leads to a more efficient use of technical information\[16]. Correlation ratios between size and measures of human and physical capital intensity were shown to be positive and significant in other studies using this data set[17].

Because the variables are highly correlated, we used *principal component analysis* to derive a general description of the relationship between them, and to obtain a clear visual representation of the grouping of firms. This technique allows us to transform the original variables into an equal number of new variables (principal components), each of which has a much higher explanatory power than the original ones. A principal component summarises sets of closely related variables. Each principal component is a synthetic variable, embodying all the original variables, and explaining part of the sample variance. The advantage of principal components is that by using just few of them (two in our analysis) we can explain a large share of the sample variance, taking into account all the original variables. Intuitively, principal components are substitutes for the original variables, but with a much larger explanatory power

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[16]. Teitel, 1984, Stiglitz ,1987, Dasgupta and Stiglitz, 1988

[17] See Baah-Nuakoh and Teal, 1993, Lall, Barba Navaretti, Teitel and Wignaraja, 1994

Table 1. Variables used for the derivation of the clusters.

	GHANA	KENYA
1. Size variables		
Sales (LSALUS)	Logarithm of Sales in 1992 (in 1992 US dollars)	Logarithm of Sales in 1993 (in 1993 US dollars)
Employment (LOGEMPL)	Logarithm of Employment in 1992 (including apprentices)	Logarithm of Employment in 1993 (including apprentices)
2. Technology indicators		
Capital labour ratio (LOGKL)	Logarithm of the ratio between the replacement value of capital and total employment in 1992 (1992 US dollars)	Logarithm of the ratio between the replacement value of capital and total employment in 1993 (1993 US dollars)
Productivity of labour (LOGPROD)	Logarithm of the ratio between value added and employment in 1992	Logarithm of the ratio between value added and employment in 1993
3. Human capital indicators		
Education of the managers (LEDMAN)	Logarithm of managers average wages in the firm	Logarithm of managers average wages in the firm
Education of technical personnel (LMEANWAG)		Logarithm of technical personnel average wage in the firm(**)
Technical personnel on total employment (SQPERSTEC)		Square of the share of technical personnel on total personnel

(*) The education variables are discrete. In order to use them for clustering we needed to transform them into continuous variables. therefore we used wages as a proxy for education (the preliminary report "Economic reform and Manufacturing Sector in Ghana" shows that the two are highly correlated). For the entrepreneurs there are obviously no wages. So we used manager wages for an equivalent level of education. The experience weight is given by the ratio between the number of years worked in the same industry and 30 years, which is the maximum experience available in the sample.
(**) Technical personnel includes foremen, technicians and skilled production workers.
Weighted average of foremen's technicians' and skilled production workers wages

than the original variables themselves[18]. The appendix provides a formal explanation of how principal components and the clusters were constructed.

The obvious question is what does each principal component represent. The ideal situation is when a component summarises sets of closely related variables. This is the case when the component is strongly correlated to a set of variables which express similar economic content. For example, if principal component 1 is only correlated to size variables, component 1 can be interpreted as a size indicator.

Components were constructed separately for each industry, because of differences in technologies. Clusters were subsequently formed on the basis of the principal components, each of them grouping firms which are homogeneous in terms of the principal component itself. Figures 3 and 4 give a graphic representation of the clusters for each industry and each country. The axes represent the two principal components used to form the clusters. Next to each figure , the correlation ratio of each component to the original variables (the rotated factor matrix) is shown. These ratios help explaining the economic meaning of the components. We have arranged the figures so that the vertical axis corresponds to the principal component mostly correlated with size variables and the horizontal axis with the principal component mostly correlated with capital intensity. Each dot represents one firm in the sample. The boxes around groups of firms represent the clusters. The clusters are called from A to D, whereby cluster A is the superior one and D the one with the poorest technology. Average capital

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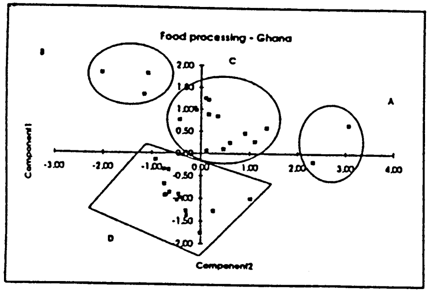
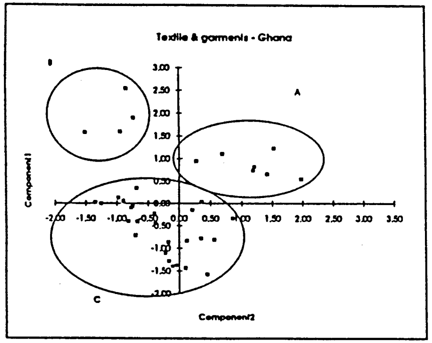
[18] Formally, a principal component is a linear combinations of the n original variables (X_1, $X_2 \dots X_n$), the coefficients of which are obtained by maximising the variance explained by the component itself.
For each set of n variables n components can be derived, under the constraint that components are not correlated between each other, i.e. principal components are orthogonal, in that they do not provide 'overlapping information': each component explains a specific amount of the sample variability.
Components can be ranked in decreasing order, according to the amount of the sample variance they explain. The selection of the number of components one wants to use is obviously arbitrary. The larger the number of components selected, the larger the amount of variance explained but the less synthetic is the information given by the analysis. There are four reasons for using the principal component instead of one of the variables. *First*, the principal component embodies the information of all the variables and not of only one. *Second*, the variance explained by the component is larger than the variance explained by any of the other variables. *Third*, the principal component also takes into account the relationship between the variables to which it is correlated and all the other variables considerd. *Fourth*, any principal component is orthogonal to all the other principal components, i.e. there is zero correlation between to principal components. Henceforth, when we consider two pricncipal components there is no duplication of information

FIGURE 3a



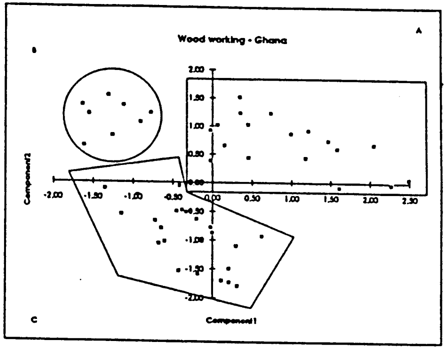
Rotated Factor Matrix		
Variables	Component1	Component2
Logk_l	0,90835	0,25782
Ledman	0,8711	0,33575
Lsatus	0,83941	0,47952
Logempl	0,87959	0,30653
Logprod	0,32615	0,94277
Pct. of variance explained	80,60%	10,60%

FIGURE 3b



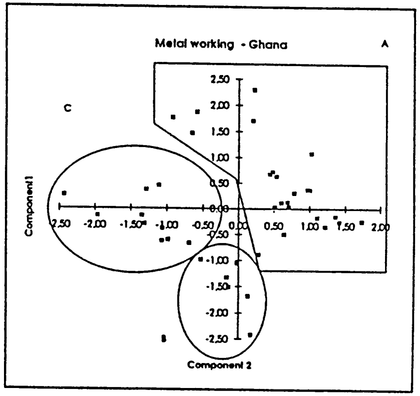
Rotated Factor Matrix		
Variables	Component1	Component2
Logk_l	0,32886	0,80641
Ledman	0,803	0,44806
Lsatus	0,69375	0,69357
Logempl	0,93826	0,23527
Logprod	0,28017	0,87567
Pct. of variance explained	73,50%	12,00%

FIGURE 3c



Rotated Factor Matrix		
Variables	Component1	Component2
Logk_l	0,78107	0,37958
Ledman	0,32636	0 8633
Lsatus	0,76768	0,52067
Logempl	0,40923	0 85315
Logprod	0,90476	0,27968
Pct. of variance explained	74,70%	11,10%

FIGURE 3d



Rotated Factor Matrix		
Variables	Component1	Component2
Logk_l	0.30258	0.92769
Ledman	0.64968	0.60358
Lsatus	0.83178	0.46639
Logempl	0.92955	0.25579
Logprod	0.67541	0.58708
Pct. of variance explained	78.30%	9.20%

TABLE 2a

Major cluster characteristics: FOOD PROCESSING - GHANA						
CLUSTER	number of	average	average	average	average	average
	firms	employees in 1993	Sales (in current U.S Dollars)	productivity (in current U.S Dollars) (a)	capital per employee (in current U.S Dollars)	education of management (in current U.S Dollars) (b)
A	2	105,50	3286266,00	19023,09	29296,92	301,21
B	3	100,33	522441,00	34,97	14782,33	88,93
C	13	64,23	244109,82	1652,37	8750,21	169,33
D	15	5,20	2757,34	155,21	576,97	2,96

TABLE 2b

Major cluster characteristics: TEXTILE & GARMENTS - GHANA						
CLUSTER	number of	average	average	average	average	average
	firms	employees in 1993	Sales (in current U.S Dollars)	productivity (in current U.S Dollars) (a)	capital per employee (in current U.S Dollars)	education of management (in current U.S Dollars) (b)
A	7	41,00	52023,06	734,0159	20881,83	139,08
B	4	92,50	20911,10	79,31	995,98	85,41
C	25	6,64	3380,73	94,13	488,07	0

TABLE 2c

Major cluster characteristics: WOOD WORKING - GHANA						
CLUSTER	number of	average	average	average	average	average
	firms	employees in 1993	Sales (in current U.S Dollars)	productivity (in current U.S Dollars) (a)	capital per employee (in current U.S Dollars)	education of management (in current U.S Dollars) (b)
A	18	122,28	452400,61	1522,08	9945,88	159,71
B	8	32,50	3483,20	79,2422	719,37	106,22
C	24	8,38	1692,66	109,16	410,46	0,02

Notes:

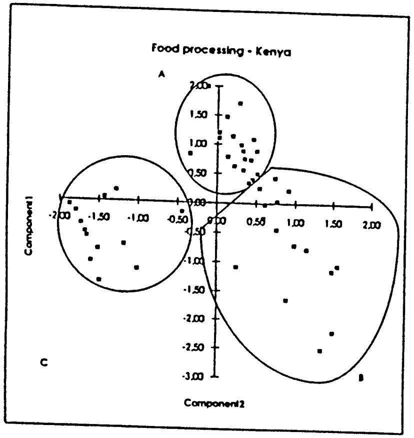
(a) Value added per employee

(b) Proxy: Management' s wages

TABLE 2d

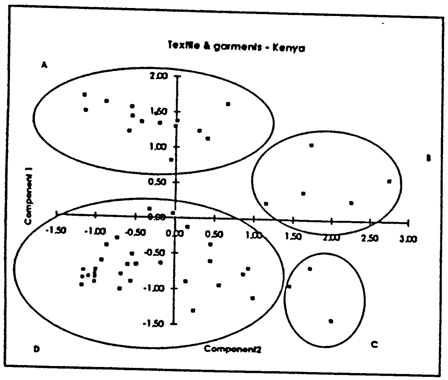
Major cluster characteristics: METAL WORKING- GHANA						
CLUSTER	number of	average	average	average	average	average
	firms	employees in 1993	Sales (in current U.S Dollars)	productivity (in current U.S Dollars) (a)	capital per employee (in current U.S Dollars)	education of management (in current U.S Dollars) (b)
A	22	62,00	427972,13	1276,51	5373,07	98,57
B	6	4,67	878,97	46,28	863,32	5,79
C	11	10,36	1057,41	37,01	160,04	15,40

FIGURE 4a



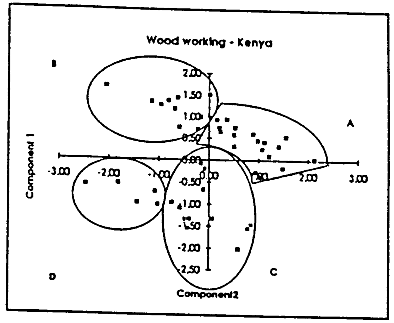
Rotated Factor Matrix		
Variables	Component1	Component2
Logempl	0,743141	0,47037
Lmeanwag	0,38587	0,88829
Sqperstec	0,06462	0,94404
Logk l	0,76795	0,15528
Lsalus	0,81329	0,20618
Logprod	0,56138	0,13709
Ledman	0,49927	0,64794
Pct. of variance explained	55,60%	14,60%

FIGURE 4b



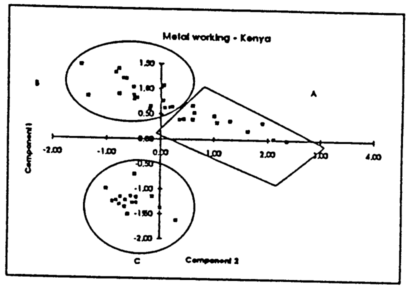
Rotated Factor Matrix		
Variables	Component1	Component2
Logempl	0,90004	0,2146
Lmeanwag	0,93559	0,16633
Sqperstec	0,91595	0,07498
Logk l	0,64285	0,45851
Lsalus	0,76513	0,49678
Logprod	0,13851	0,95455
Ledman	0,76629	0,33479
Pct. of variance explained	68,60%	12,60%

FIGURE 4c



Rotated Factor Matrix		
Variables	Component1	Component2
Logempl	0.85305	0 30926
Lmeanwag	0.87916	0 38311
Sqperstec	0.78621	0 29346
Logk_l	0.27955	0 81856
Lsalus	0.77821	0 4846
Logprod	0.33381	0 75931
Ledman	0.86103	0 28487
Pct. of variance explained	70.00%	9 20%

FIGURE 4d



Rotated Factor Matrix		
Variables	Component1	Component2
Logempl	0.69642	0.55456
Lmeanwag	0.93144	0.30018
Sqperstec	0.90607	-0.0025
Logk l	0.72571	0.51111
Lsalus	0.69944	0.64326
Logprod	0.10879	0.93522
Ledman	0.10879	0.93522
Pct. of variance explained	72,60%	12,50%

TABLE 3a

Major cluster characteristics: FOOD PROCESSING - KENYA

CLUSTER	number of firms	average employees in 1993	average Sales (in current U.S Dollars)	average education of technical personnel (in current U.S Dollars) (a)	average share of technical personnel on employment (b)	average productivity (in current U.S Dollars) (c)	average capital per employee (in current U.S Dollars)	average education of management (in current U.S Dollars) (d)
A	16	309,88	5630957,13	76,97	5,20%	12787,93	32368,49	835,78
B	18	68,28	1202118,05	46,21	9,89%	2697,63	12739,28	394,61
C	12	9,69	86632,47	0,69	0,23%	1658,75	5565,27	44,67

TABLE 3b

Major cluster characteristics: TEXTILE & GARMENTS - KENYA

CLUSTER	number of firms	average employees in 1993	average Sales (in current U.S Dollars)	average education of technical personnel (in current U.S Dollars) (a)	average share of technical personnel on employment (b)	average productivity (in current U.S Dollars) (c)	average capital per employee (in current U.S Dollars)	average education of management (in current U.S Dollars) (d)
A	15	364,60	1687227,62	27,59	11,60%	1597,59	12945,98	457,73
B	6	61,20	1676201,80	33,73	8,09%	7901,18	12378,52	680,44
C	3	6,67	82636,20	0	0,00%	5276,94	4713,41	103,47
D	29	6,55	28171,67	0	0,00%	942,44	1537,42	89,97

TABLE 3c

Major cluster characteristics: WOOD WORKING - KENYA

CLUSTER	number of firms	average employees in 1993	average Sales (in current U.S Dollars)	average education of technical personnel (in current U.S Dollars) (a)	average share of technical personnel on employment (b)	average productivity (in current U.S Dollars) (c)	average capital per employee (in current U.S Dollars)	average education of management (in current U.S Dollars) (d)
A	18	72,17	398098,97	32,22	17,52%	2755,52	7143,36	321,62
B	10	79,80	389545,79	43,36	25,85%	954,16	2782,23	527,05
C	13	8,38	25596,99	0,55	1,26%	591,55	1943,94	50,17
D	5	6,00	2449,64	0.00	0.00%	152,09	290,09	0.00

TABLE 3d

Major cluster characteristics: METAL WORKING - KENYA

CLUSTER	number of firms	average employees in 1993	average Sales (in current U.S Dollars)	average education of technical personnel (in current U.S Dollars) (a)	average share of technical personnel on employment (b)	average productivity (in current U.S Dollars) (c)	average capital per employee (in current U.S Dollars)	average education of management (in current U.S Dollars) (d)
A	12	324,75	6213072,00	75,67	10,11%	10099,69	29555,14	762,32
B	20	65,95	361211,20	62,52	28,96%	2694,68	13863,91	522,56
C	17	3,71	5209,16	0	0.00%	1126,01	634,49	11,96

Notes:

(a) Proxy: Weighted average of foremens', technicians' and skilled production workers' wages

(b) Share of foremen, technicians and skilled production workers on total employment of the firm

(c) Value added per employee

(d) Proxy: Management's wages

intensity and human capital increase when we move from D to A[19]. The number of clusters vary between two and four, depending on the industry and the country. Tables 2 and 3, give the average values for some key variables characterising the firms in the clusters.

A sets of very interesting result can be derived from the analysis

First, the four industries in both countries are characterised by clear cut technological clusters. Clusters group firms with similar values of the technological and human capital indicators. This suggests that there are intra-industry technological gaps.

Second, in the four industries and in both countries, there are always at least two clusters, whereby the inferior one (with lower capital and skill intensity[20]) is always composed of micro enterprises. These firms are usually side of the road workshops, with uneducated entrepreneurs and no managerial structure. In Kenya the technological structure of the clusters is quite neat, with physical and human capital intensity gradually increasing from the lower to the top clusters. In Ghana the picture is dirtier and only two clusters per industry can be easily characterised. In each industry, in fact, there is a cluster with medium-high physical and human capital intensity, but very poor productivity. These firms are probably the outcome of distorted incentives, before structural adjustment[21].

Third, the structure and the nature of the clusters is different for each of the industries and depends on the features of the technology in the industry itself. This result is especially evident for the Kenyan sample (Figure 4 and Table 3). In particular, the pattern changes when we compare the two capital intensive industries (metal and food) and the two labour intensive ones (wood and textile). The change in the production technology when we move from the lowest cluster is generally more considerable for the capital intensive ones. Average capital intensity in the second worse cluster is much lower in the labour intensive sectors than in the capital intensive ones and there is no technical personnel. This result would show that in

19. Note that the industries are defined in a very broad way. Therefore, we face the risk that differences in technology reflect deifferences in products. For example, in the case of the textile industry, we might expect clothing firms to be in the lower cluster and textile firms in the upper one. This is not the case. There is not a clear association between clusters and types of products.

20. Skill intensity refers to the level of education of managers and technicians

21. These clusters of inefficient medium high capital intensive firms did not emerge in a previous cluster analysis carried out for Ghana using the same data set (Lall, Barba Navaretti, Teitel and Wignaraja, 1994), where productivity was not included in the analysis.

simple industries, at the lower end of the technological spectrum, there is an opportunity for some technological upgrading because the discrete jump in the technology is smaller. The same opportunity is not available for firms in capital intensive industries: upgrading from the micro cluster implies a more radical change in technology. Metal working and food processing firms in the top clusters (A) are also more physical and human capital intensive than the top firms in wood working and textile. Thus, in capital intensive industries the spectrum of the technological opportunities is wider.

Fourth, there is, as expected, a positive and consistent association between size and human and physical capital intensity. This result is clear for every industry and for both countries. Firms in the top technological clusters are on average larger. However, size does not explain all differences in technology. First, capital intensity (measured by the capital labour ratio or by labour productivity) has explanatory power of the sample variance which is independent of size (see the rotated factor matrix in figures 3 and 4). Second, some of the clusters observed differ in terms of technology and human capital, but not in terms of size. Take, as an example clusters A and B in food processing in Ghana or A and B in wood working in Kenya[22].

3.2. Technological clusters, market segmentation and initial conditions

The theoretical model in section two postulates that, given different technological advantages, firms may choose different technologies and, subsequently, different market segments. The scope of this section is to test these hypothesis. The analysis will be carried out in two steps. The first one will consist in examining whether technological clusters can be consistently associated to differences in initial endowments (proxying the technological advantage) and factor market segments. The second step will focus on investigating the causal link between technological clusters, initial conditions and factor market segmentation.

Previous studies based on the same data set provide direct and indirect evidence that small and large firms face different prices, particularly for labour and finance[23]. Here, we are

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[22] These results confirm the high correlation ratios between the variables considered, not reported here (see Lall, Barba Navaretti, Teutel and WIgnaraja 1994).

[23]. Baah-Nuakoh and Teal, 1993, Lall, Barba Navaretti, Teitel and Wignaraja, 1994, Departments of Economics, University of Gothenburg and University of Nairobi, 1993, Economic and Social Institue, Free University, Amsterdam and Department of Economics, University of Zimbabwe.

not particularly concerned with prices. Rather, we expect firms in different clusters to use market segments reflecting differences in factor quality (e.g. education of labour), channels of acquisition (e.g. formal or informal hiring procedures) and contractual relationships (apprentices vs. full time employees). Choices of different segments may well be the consequences of differences in prices or entry barriers. Yet, as postulated by the model, different choices may persist even when differences in prices and other constraints are eliminated, as far as different technological advantages persist.

We will use three indicators of initial conditions, which may well proxy the technological advantage. First, the *education of the entrepreneur*. In backward contexts, where the local environment is not conducive to technological upgrading, it is often noticed that individuals have a crucial role as 'technological cathalizers' within the firm. In doing so they overcome the imperfections of the market for technology and the lack of internalised transactions in poorly organised firms. Second, we will consider whether there is a *foreign or a state share in the equity* of the firm, the assumption being that foreign and state ownership give access to more resources, in terms of finance, skills, information. Third we will consider the *ethnic origin of the local entrepreneur*, for the case of Kenya. Here, non-African entrepreneurs, especially Asians, own a large share of industry. This is the result of the colonial history of this country and of the perverse effect of indigenisation policies which, by restricting Asians in trade, forced them to move into light industry. There are, therefore, good reasons to expect local firms with non-African entrepreneurs to have a better technological performance: the owner is likely to have longer industrial experience and better connections overseas to access capital and technology.

The analysis of factor market segmentation is particularly focused on the *labour market*. We will test whether firms in different clusters use different channels for workers recruitment, whether they establish different employment relations and whether they have different institutional arrangements for training. We consider two major channels of recruitment: vocational training schools and other formalised channels are confronted with informal, 'word of mouth' channels. The existence and the pervasiveness of apprenticeship will reflect differences in the employment relationship and in the institutional arrangements for training.

We will also analyse the market for *capital equipment*. For Ghana, we will consider whether the source of information on the capital equipment purchased is local or foreign. For

Kenya, we will examine whether local or foreign equipment was actually purchased (homogeneous data for the two countries are not available). The assumption is that firms have a different access to foreign sources when markets are characterised by imperfect information. Finally, we will look at the *financial market*. It will be checked whether firms finance their purchase of capital equipment through banks, other formal financial institutions and supplier credit or through informal channels and their own savings.

3.2.1. Tests of Association

All the variables considered are discrete. We now run tests of associations for each industry and for each country between the clusters and our indices of initial conditions and factor market segmentation [24]. The results are presented in Tables 4a and 4b. The degree of association was initially tested for couples of clusters and then by grouping clusters together. Only significant results are reported.

First, in every industry there is a very clear threshold where the jump to a superior cluster is associated with significant differences in initial endowments and or factor segmentation. Beyond or before the threshold associations are mostly not significant. This means that there are opportunities for technological upgrading at the lower and at the top end of the technology spectrum which do not necessarily require changes in factor market segments and initial endowments.

Second, initial conditions are significant. Clusters beyond the threshold are always associated with entrepreneurs with a level of education higher than or equal to secondary school (except for woodworking in Ghana and food processing in Kenya). The ethnical origin of the entrepreneur is the variable most significantly associated with the passage through the threshold in Kenya (the same variable is not available for Ghana). African entrepreneurs are largely concentrated in the inferior technological clusters. Foreign ownership is significant for three industries in Kenya and two in Ghana. State ownership for one each in the two countries.

Third, segmentation of the labour market is also significant. This is true if we look at the source of workers recruitment which changes significantly from informal into formal for all the industries in Ghana and for two of them in Kenya. The role of apprenticeship is striking in

[24]. A test of association for discrete variables is equivalent to a correlaton analysis for continuous variables.

TABLE 4a

Cluster and significant Market Segmentation-GHANA

(Measure of association between the clusters, initial endowments and factor market segmentation, and related significance)

	Food processing				Textile & garments			
	cluster A vs. C		cluster A, B and C vs. D		cluster A and B vs. C		cluster A vs. C	
Variables	Cramer's V (a)	Signif. (b)	Cramer's V (a)	Signif. (b)	Cramer's V (a)	Signif. (b)	Cramer's V	Signif. (b)
Source of Capital Acquisition (c)	0.42361	**	0.35806	no	n.a		n.a	
Source of Financing (d)	0.09245	no	0.31269	*	0.01446	no	0.1005	no
Source of workers' Recruitment (e)	0.02159	no	0.60123	***	0.32329	*	0.4714	**
Use of apprentices (f)	n.a	n.a	0.57735	no	0.08792	no	0.16903	no
Use of apprentices (g)	n.a	n.a	0.4	no	0.56666	***	0.59649	***
Entrepreneur's education level (h)	0.3333333	no	0.60698	***	0.3934	*	0.40254	*
Ownership structure: public vs. private (j)	0.36706	no	0.38576	**	0.36664	**	n.a	n.a
Ownership structure: foreign vs. national (k)	0.32388	no	0.23238	no	0.36564	**	0.48795	***

	Wood working				Metal working	
	cluster A and B vs. C		cluster A vs. B		clusters A vs. B and C	
Variables	Cramer's V (a)		Cramer's V (a)		Cramer's V (a)	Signif. (b)
Source of Capital Acquisition (c)	0.4292	**	0.03912	no	0.33113	*
Source of Financing (d)	0.43994	***	0.11835	no	0.37952	**
Source of workers' Recruitment (e)	0.28022	**	0.27778	no	0.52293	***
Use of apprentices (f)	0.22942	no	0.13593	no	0.21926	no
Use of apprentices (g)	0.48187	***	0.50488	**	0.68599	***
Entrepreneur's education level (h)	0.25598	no	0.4714	**	0.65315	***
Ownership structure: public vs. private (j)	0.19612	no	0.19245	no	0.25376	no
Ownership structure: foreign vs. national (k)	0.38764	***	0.21678	no	0.23602	no

Notes:

(a) Cramer's V is defined as the square root of Pearson's chi-square previously divided by the sample's size times the minimum between the number of rows and columns (minus 1) of the contingency table

(b) Observed Significance Levels *** = not less than 99%; ** = not less than 95%; * = not less than 90%; no = less than 90%

(c) Binary variable which assumes value 1 if the most important source of information about the most recent acquisitions of capital equipment of the firm was among the following: independent supplier of plant and equipme foreign joint venture partner/parent company, foreign buyers, foreign technical consultants, foreign trips and assumes value 0 if the most important source of information about the most recent acquisitions of capital equipment of the firm was among the following: publications, trade fairs, business associations, other local firms and technology institutions.

(d) Binary variable which assumes value 1 if bank and supplier credit are among the main sources of financing of the firms and assume value 0 if not

(e) Binary variable which assumes value 0 if the sources of workers' recruitment are among the following: suggestion from supplier or business associate, suggestion from relatives or friends of the owner or of the current employee, word of mouth, it assumes value 1 if the sources of workers' recruitment are among the following: labour office, formal advertising, trade or technical schools.

(f) Binary variable which assumes value 1 if apprentices are not employed in the firm and assumes value 0 if they are. Missing answers are not included

(g) Binary variable which assumes value 1 if the percentage of apprentices on total employment in the firm is less than 30%, and assumes value 0 if it's more or equal to 30% in food processing sector. For textile & garments sector, the boundary is set at 50%, while for wood working and metal working sectors, it is set at 80%. Missing answers are not included.

(h) Binary variable which assumes value 1 if the education level reached by the entrepreneur is not below an university degree, 0 if it is not above a secondary school diploma

(j) Binary variable which assumes value 1 if the firm is totally or partially owned by the State and 0 if it is entirely private

(k) Binary variable which assumes value 1 if the firm is entirely or partially owned by foreigners and 0 if it is exclusive property of Kenyan owners.

TABLE 4b

Cluster and significant Market Segmentation-KENYA

(Measure of association between the clusters, initial endowments and factor market segmentation, and related significance)

	Food processing				Textile & garments	
	clusters A and B vs. C		cluster A vs. B		clusters A and B vs. C and D	
Variables	Cramer's V (a)	Signif. (b)	Cramer's V (a)	Signif. (b)	Cramer's V (a)	Signif. (b)
Source of Capital Acquisition (c)	0.5164	***	0	no	0.67446	***
Source of Financing (d)	0.14548	no	0.24019	no	0.46429	*
Source of workers' Recruitment (e)	0.33305	**	0.35564	**	0.15912	no
Use of apprentices (f)	0.52381	*	0.35355	no	0.38925	no
Entrepreneur's ethnical origin (g)	0.34007	**	0.12309	no	0.69222	***
Entrepreneur's education level (h)	0.19537	no	0.30241	no	0.38126	***
Ownership structure: public vs. private (j)	0.12666	no	0.26517	no	0.25298	*
Ownership structure: foreign vs. national (k)	0.04697	no	0.2486	no	0.33311	**

	Wood working				Metal working			
	clusters A and B vs. C and D		cluster A vs. B		clusters A and B vs. C		cluster A vs. B	
Variables	Cramer's V (a)	Signif. (b)	Cramer's V (a)	Signif. (b)	Cramer's V (a)	Signif. (b)	Cramer's V (a)	Signif. (b)
Source of Capital Acquisition (c)	0.07559	no	0.02144	no	0.3133	**	0.2875	no
Source of Financing (d)	0.07559	no	0.25	no	0.63738	***	0.09245	no
Source of workers' Recruitment (e)	0.11528	no	0.2582	no	0.45374	***	0.48795	***
Use of apprentices (f)	0.49099	*	0.14907	no	n.a	n.a	0.29277	no
Entrepreneur's ethnical origin (g)	0.713333	***	0.05025	no	0.66204	***	0.23681	no
Entrepreneur's education level (h)	0.52911	***	0.46098	**	0.44656	***	0.09221	no
Ownership structure: public vs. private (j)	n.a	n.a	n.a	n.a	0.11099	no	0.26261	no
Ownership structure: foreign vs. national (k)	0.33968	**	0.08607	no	0.39135	***	0.1	no

Notes:

(a) Cramer's V is defined as the square root of Pearson's chi-square previously divided by the sample's size times the minimum between the number of rows and columns (minus 1) of the contingency table

(b) Observed Significance Level: *** = not less than 99%; ** = not less than 95%; * = not less than 90%; no = less than 90%

(c) Binary variable which assumes value 1 if the most recent acquisitions of capital equipment of the firm was foreign or mostly foreign and assumes value 0 if it was local or mostly local or imported but bought locally.

(d) Binary variable which assumes value 1 if bank and supplier credit are among the main sources of financing of the firms and assume value 0 if not

(e) Binary variable which assumes value 0 if the sources of workers' recruitment are among the following: suggestion from supplier or business associate, suggestion from relatives or friends of the owner or of the current employee, word of mouth, it assumes value 1 if the sources of workers' recruitment are among the following:

(f) Binary variable which assumes value 1 if apprentices are not employed in the firm and assumes value 0 if they are. Missing answers are not included

(g) Binary variable which assumes value 1 if the owners' ethnical origins are Asian, European or Middle - Eastern and assumes value 0 if the owners' ethnical origins are African.

(h) Binary variable which assumes value 1 if the education level reached by the entrepreneur is not below an university degree, 0 if not above a secondary school diploma (in metal working and textile & garments sectors) and assumes value 1 if the education level reached by the entrepreneur is not below a secondary school diploma, and 0 if below (in food processing and wood working sectors)

(j) Binary variable which assumes value 1 if the firm is totally or partially owned by the State and 0 if it is entirely private

(k) Binary variable which assumes value 1 if the firm is entirely or partially owned by foreigners and 0 if it is exclusive property of Kenyan owners.

Ghana. We use two indicators; the first one is whether firms use apprentices; this is not significant, mostly because a very large proportion of firms in all clusters use them (besides for food processing). The second one is the share of apprentices on total employment in the firm. The share that changes significantly beyond and above the threshold is 50% for textile and 80% for metal and wood working. This result implies that in the last two industries at least 80% of the work-force in the lower clusters is made of apprentices. Apprenticeship is much less widespread in Kenya.

Fourth, firms significantly change factor market segment also for capital equipment and finance. Firms in the inferior clusters gather information about equipment (in Ghana) or buy equipment (in Kenya) from local sources. At the same time these firms do not get credit from banks or suppliers. Retained earnings or personal savings of the owner are by large the most frequent source of finance for all the firms in all the clusters.

The analysis of association provides a good assessment of the relationship between changes in technological clusters, initial endowments and market segments. Up to this point the analysis had to be carried out for each industry separately, because technology is industry specific and we cannot map it for the whole sample. We can now divide firms between those which are in clusters above and those which are in clusters below the technological threshold, in each industry. Thus, the cluster analysis, joined with the analysis of association, allows us to normalise industry specific technological differences across the whole sample, and divide firms into two groups, the weak ones (firms with poor technology) and the strong ones(firms with more complex technologies). We can now use the whole sample in each country to investigate into the causal relationship between the three sets of variables considered, technological clusters, initial conditions and factor market segmentation.

3.2.2 Causal Links: Probit Analysis

Following the theoretical model we proceed in two stages. First we test whether technological clusters can be significantly explained by initial conditions. Then, we examine whether technological clusters are significant determinants of factor market segmentation, i.e. whether factor market segments are chosen endogenously, following the choice of the technology.

TABLE 5a

Probit analysis: Initial endowments as determinants of technological clusters - GHANA				
Log likelihood	-67,87089			
Number of observations	130			
Chi squared (3 d.f.) (a)	39,24			
Prob. > Chi squared	0,00			
Pseudo R squared	0,2243			
Dependent variable	Clustech (b)			
Variable	Coefficient	Std. Err.	Z	P value
edemp1 (c)	1,2822	0,2787561	4,6	0,0001
foreigno (d)	0,6876314	0,3925959	1,751	0,08
dumtext (e)	-0,6385647	0,3056685	-2,089	0,037
constant	-0,6296006	0,161863	-3,89	0,0001

TABLE 5b

Probit analysis: Initial endowments as determinants of technological clusters - KENYA				
Log likelihood	-66,781459			
Number of observations	158			
Chi squared (3 d.f.) (a)	85,24			
Prob. > Chi squared	0,00			
Pseudo R squared	0,3896			
Dependent variable	Clustech (b)			
Variable	Coefficient	Std. Err.	Z	P value
ethnica (f)	1,8044856	0,2586169	6,979	0,0001
edemp2 (g)	1,050394	0,3582383	2,932	0,003
dumtext (e)	-0,8383768	0,2911143	-2,88	0,004
constant	-0,8321228	0,1930719	-4,31	0,0001

Notes

(a) Degrees of freedom

(b) Binary variable which assumes value 1 if the firm is in the more advanced technical clusters, 0 otherwise

(c) Binary variable which assumes value 1 if the education level reached by the entrepreneur is not below a secondary school diploma, 0 if it is below

(d) Binary variable which assumes value 1 if the firm is entirely or partially owned by foreigners and 0 if it is exclusive property of national owners.

(e) Dummy variable for the textile sector

(f) Binary variable which assumes value 1 if the owners' ethnical origins are Asian, European or Middle - Eastern and assumes value 0 if the owners' ethnical origins are African.

(g) Binary variable which assumes value 1 if the education level reached by the entrepreneur is not below an university degree, 0 if it is below

TABLE 6a

Probit analysis: technological clusters as determinants of factor markets segmentation - GHANA				
Log likelihood	-67,69			
Number of observations	153			
Chi squared (3 d.f.) (a)	63,30			
Prob. > Chi squared	0,00			
Pseudo R squared	0,32			
Dependent variable	(factor) (b)			
Variable	Coefficient	Std. Err.	Z	P value
clustech (d)	1,52	0,26	5,848	0,0001
dumwood (e)	-1,64	0,45	-3,626	0,0001
dumtext (f)	-1,89	0,47	-3,985	0,0001
dummeta (g)	-1,29	0,47	-2,741	0,006
constant	1,11	0,40	2,773	0,006

TABLE 6b

Probit analysis: technological clusters as determinants of factor markets segmentation - KENYA				
Log likelihood	-88,351495			
Number of observations	163			
Chi squared (4 d.f.) (a)	85,24			
Prob. > Chi squared	0,00			
Pseudo R squared	0,2021			
Dependent variable	(factor) (c)			
Variable	Coefficient	Std. Err.	Z	P value
clustech (d)	1,279905	0,2362776	5,417	0,0001
dumfood (h)	0,8914735	0,3147993	2,832	0,005
dummeta (g)	0,8449717	0,3068837	2,753	0,006
dumtext (f)	0,7274634	0,309141	2,353	0,019
constant	-1,212393	0,2759766	-4,393	0,00

Notes

(a) Degrees of freedom

Dependent Variables

(b) Binary variable which assumes value 1 if the percentage of apprentices on total employment in the firm is less than50%, OR use formal rworkers' recruitment sources, and 0 otherwise

(c) Binary variable which assumes value 1 if the firm uses formal workers' recruitment sources OR the most recent acquisitions of capital equipment of the firm was foreign or mostly foreign and assumes value 0 if it was local or mostly local or imported but bought locally.

(d) Binary variable which assumes value 1 if the firm is in the more advanced technical clusters, 0 otherwise

(e) Dummy variable for the wood working sector

(f) Dummy variable for the textile sector

(g) Dummy variable for the metal working sector

(h) Dummy variable for the food processing sector

To do so, we will carry out a Probit analysis. Probit tests, for dichotomous variables, the probability that the dependent variable is explained by the independent ones. The analysis is carried out separately for the two countries, because of the differences in the variables available. To control for sector specific effects, which are not captured by the variables useed, we introduce sector dummies (these dummies are dropped when not significant).

We start with the determinants of the technological clusters The dependent variable (clustech) is dichotomous and takes value 1 if firms belong to the group of the strong ones and 0 to the group of the weak ones. The explanatory variables (also dichotomous) are our indices of initial conditions which take value 1 for initial conditions that we expect to be associated with the top group and zero otherwise. Only the best performing probits are shown in tables 5a and 5b.

Results are particularly satisfactory for Kenya (in terms of Log-likelihood and pseudo R squared), and acceptable for Ghana. The education (edempl) and the ethnic origin (ethnica-for Kenya) of the entrepreneur are extremely significant. The performance of the ethnic variable is quite remarkable.

Tables 6a and b examine whether technological clusters are significant determinants of factor market segments. Given that factor market segmentation is the dependent variable, we need to merge dummies related to different factor markets into a single variable (factor). For Kenya we construct a variable which takes value 1 if the firm uses formal sources of workers' recruitment or purchases capital equipment abroad and zero otherwise. For Ghana, the dependent variable takes value 1 if the firm uses formal sources of workers' recruitment or it has a share of apprentices below 50% and zero otherwise. We have only considered the market segments most significantly associated with the technological thresholds. The independent variable (clustech) takes value 1 if firms are in the top technological clusters and zero otherwise. As we can see, technological clusters significantly explain factor market segmentation.

To sum up, the empirical analysis supports the predictions of the theoretical model. Initial conditions affect the choice of the technology. In turn, firms, following the choice of the technology, endogenously choose different factor market segments.

4. Policy dilemmas: picking the strong or supporting the weak

The analysis conducted so far bears important policy implications. The most straightforward one is that there are reasons for technological gaps other than imperfections and constraints in factor markets like labour and finance. In particular, policy should also focus on compensating differences in initial conditions.

This line of action would however put politicians in front of a dilemma: overall technological development vs. a rise in unemployment in the short term. The nature of the dilemma can be easily understood, in terms of the model developed in section 2. If, for example, the labour market is liberalised, and therefore the cost of formally hired labour is reduced, the ratio c_e/c_u.declines[25]. The impact is twofold. On the one hand, the technological gap between superior and inferior firms increases (from 2.11). This is because the differential in labour cost counterbalances firm specific factors in the choice of the optimal quality. On the other hand, more firms will enter the superior labour market segment, because line $(c_e/c_u)^2$ shifts down in figure 2). In fact, firms in the intermediate range (i.e. with intermediate values of γ) face multiple equilibria, depending on the relative cost of skilled labour. In static terms, entry into the superior labour market segment leads to a reduction in the technology gap for firms in this group[26]. In dynamic terms the availability of educated labour will lead to faster learning and technological upgrading. Hence, following the reduction in c_e, high tech firms will strengthen their technological advantage and some firms will manage to upgrade. However, the gap with those firms that still do not manage to upgrade will increase even further. The competitive position of the latter will deteriorate and some of them will be pushed out of the market. Given that the informal sector is one of the largest employer in many developing countries, the impact of such policies should be carefully assessed.

Similar problems emerge if we address another critical constraint to technological upgrading, i.e. the non existence or the imperfections of the markets for technology. We have in

[25] The assumption that ce and cu.are constant implies that labour supply is infinitely elastic. In backward countries this is never the case for educated labour. Policies aimed at increasing the supply of educated labour may also lead to a reduction in the cost of educated labour.

[26] It can be shown that v declines when j enters the superior labour market segment if $\alpha_{ju}/\alpha_{je} > Ce/Cu$ See Barba Navaretti, 1994a for a demonstration

fact listed three sets of determinants of the firm specific technological advantage: different initial endowments, inefficient internalised transactions, imperfections in markets for technological inputs. We have seen that the market for capital equipment is clearly segmented in our survey. In background contexts, markets for technology are not only imperfect, but very often missing. And the more markets are missing, the more technological transactions are internalised. Therefore, in background countries those combinations of inputs and other intangible factors which may lead to higher technological capabilities are exceptional and firm specific even for very simple technologies. This is why individual entrepreneurs seem to be having a fundamental role in the more technologically competent firms.

The role of technological policies can be easily shown by slightly modifying the model of section 2. We assume, for example, that technical assistance services are set up in the country where our two firms are based. Local supply of such services (private or public) reduces the cost of technical assistance, that before could only be supplied from abroad. Thanks to these institutions the two firms can purchase technological inputs at a lower cost. The firm specific advantage coefficient declines by $\mu_{i,j}$ for each firm. The sunk cost for achieving product quality also declines and it is now given by:

$$F(q)_i = (\alpha_i - \mu_i)q_i^2 \qquad (6.1)$$

where $\mu_i = \mu_i\,(g, \gamma_i)$

for $\delta\mu_i/\delta\gamma_i < 0$ and $\delta\mu_i/\delta g > 0$

where g is government expenditure in the institution.

The assumption that the discount in the investment in technology (quality) is larger the lower the firm technological advantage, implies that poor technology firms benefit more from the local supply of technical assistance. In other words, we assume that the cost for technical assistance was higher for the poor quality firm before the new services were locally set up. As an example, imagine that the high tech firm is a multinational that has sufficiently skilled manpower to compensate for the unavailability of technical services locally or that can get technical assistance from its parent company. In contrast, the poor technology firm is a locally owned firm that can only import technical services from abroad.

As a result, the new technological gap is given by:

$$v = qj/qi = [(\alpha_i - \mu_i)/(\alpha_j - \mu_j)](c_i/c_j) \qquad (6.2)$$

Given that, according to our assumption, the reduction in costs deriving from the technical assistance services is larger for the poor quality firm j, i.e. $\mu_i<\mu_j$, the effect of the new institution will be to reduce the quality gap. Note that this result crucially depends on the assumption that $\delta\mu_i/\delta\gamma_i < 0$. If government intervention is equally beneficial to all firms (i.e. for $\delta\mu_i/\delta\gamma_i = 0$), inter-firm gaps within the country are likely to increase. In other words, firms which have a technological advantage will benefit more from government intervention and, unless product markets are segmented, poor technology firms are more likely to be pushed out of business. Under this assumption, the introduction of technical assistance services has the same effect than the deregulation of the labour market analysed above.

Informal firms are generally perceived either as the reservoir for marginal urban employment or the seed bed of the entrepreneurial and technological dynamo. Our analysis shows that probably both types of firms are part of the informal sector. This conclusion is supported by the existence of more than two clusters in each of the industries analysed. In this context, policy objectives must be spelled out very clearly. Policies for technological upgrading would favour firms in the intermediate technological range, increasing their probability to move up into the modern segment of the industry. These policies should however be coupled with interventions aimed at preserving employment in firms at the bottom of the technological scale.

5. Conclusions

In this paper we have shown that intra-industry technological gaps, like the one observed in sub-Saharan Africa, may emerge because of the process of technological development per se. There are three theoretical reasons why the process of technological development per se may cause technological gaps. The first one is that technological inputs are many, characterised by market imperfections and often missing markets. The second one is that, given the lack of external markets, technological transactions are often internalised within the firm, leading to generally inefficient outcomes. The third one is that firms may greatly differ in their initial endowments of technological capabilities.

Imperfections in other factor markets (like the labour market), generally addressed by liberalisation and price denominated policies, may also cause technological gaps. However, the removal of such imperfections is unlikely to foster technological development, unless the determinants of the firm specific technological advantage are directly tackled.

The empirical analysis, based on a recent survey of 350 enterprises in Ghana and Kenya, shows that it is possible to define technological thresholds, characterised by very significant shifts in technology (physical and human capital intensity), initial endowments (education and ethnic origin of the entrepreneur, foreign and state ownership), and factor market segments (labour, capital equipment and finance).

This paper is particularly concerned with the relationship between technological gaps and the labour market. Firms above (the strong ones) and below (the weak ones) the technological threshold, hire labour through different channels and train workers with completely different institutional arrangements (apprenticeship vs. vocational training). These shifts may well be determined by different wages of workers with the same degree of education, which are generally higher for larger firms. However, this paper shows that the choice of different segments of the labour market may still emerge when firms are not constrained in the choice of the labour market segment and when they all face the same price relative to labour quality.

Policy implications are important. Price denominated policies (particularly in those markets traditionally addressed by economic policy) may not provide a sufficiently conducive environment. Sometimes they could even increase technological gaps. Policies specifically geared to the process of technological development are also necessary. However, two qualifications are useful. First, such policies may address some of the market imperfections characterising the market for technological capabilities. Other imperfections cannot be addressed by policy makers and therefore cause a persistence of technological gaps, independently of policy action. Second, technological policies may lead to an overall technological upgrading but, at the same time, increase the technological gap between firms at the opposite ends of the technological spectrum. Hence, policy makers are faced with a *promoting the strong* vs. *supporting the weak* dilemma. Interventions not specifically targeted to the lower end of the technology spectrum may push weaker firms out of business, with serious employment implications.

Appendix- A methodological note

A1. Principal components

Five theoretically important (imputed) quantitative variables were selected for Ghana and seven for Kenya; thus we had a data matrix of order (157,5, for Ghana and 193,7 for Kenya). We focus on the case of Ghana to examplify our work. Since we wished to get a clear visual representation of the information contained in this matrix, and since there was a quite high correlation among variables belonging to certain homogeneous economic subgroups, principal component analysis could allow us to reduce the number of variables without losing much of the statistical information contained in the original 157,5 modalities.

Let X(157,5) be the original data matrix, the first principal components of X(157,5) is, by definition:

$$P(1) = \Sigma_i\, a_{i1} * X_i = X(157,5)a1$$

where a1' is a row-vector with elements (a11,a21,....,ak1) , and Xi a column-vector of X(157,5); a1 is determined by the following maximization process:

$$\max (s^2{}_1) \quad \text{s.t. } a1'a1=1$$

Where $s^2{}_1$ is the sample variance of P(1).The first principal component P(1) is therefore a linear combination of the k original variables (X1,X2,...,Xk) with coefficients equal to the elements of the eigenvector associated to the greatest eigenvalue of the variance-covariance matrix of X(157,5).

The second principal component P(2) = X(157,5)a2 is computed as the first one, maximizing $(s^2{}_2)$

$$\text{s.t.} \quad \begin{array}{l} a2'\, a2=1 \\ a1'\, a2=0 \end{array}$$

where the second constraint means that component P(1) and P(2) are not correlated. The same procedure applies for the other principal components. (Note that the number of components of a matrix is equal to its rank i.e. to the number of its noncorrelated columns).

There are two major properties of principal components which it's important to stress:

i) They are orthogonal, thus there is no 'overlapping' information among them: each explains a specific amount of the sample variability.

ii) Since the result of the optimization shown above is:

$$\max (s^2{}_i) = l(i) = Var(P(i))$$

where l(i) is the i-th eigenvalue in decreasing order, then,

$$l(i) / \Sigma_i\, l(i)\ 100$$

will be i-th's principal component contribution to the explanation of original data total variability. We have thus obtained 5 (=rank of X(157,5)) new (noncorrelated) variables of decreasing importance and maximum variance:

We chose to show the first two principal components, retaining a percentage of total original data's variability equal to $l(1)+l(2)/\Sigma i\ l(i)\ 100$ (in our case never less than 85% for Ghana and 60% for Kenya);

A rotation phase of components analysis attempts to transform the initial factor structure matrix into one that is easier to interpret, by rotating components' axes Varimax, the algorithm we used, attempts to minimize the number of variables which are correlated with one component, preserving distances between them.

A2 Cluster analysis

Clustering algorithms were run at an industry level because no clusters could be detected at the whole sample level.

The problem was the choice of the algorithm that was to be used. Empirical studies show that different algorithms give the same clusters, if groups posses a spheric shape. Particularly, splitting methods, which form groups by dividing the original statistical population, are not likely to determine non-spheric clusters, while aggregating algorithms, which aggregate objects around predetermined centers, can only create non-spheric clusters; As shown by biplots, some clusters don't have a spheric shape. For this reason an aggregating method was chosen. Aggregating methods operate in the following way:

- initially n clusters (c1,c2,...,cn) - each made up of one element of the population - are considered;

- then a new partition is built up by minimizing d(ci,cj) relatively to i and j, (where d is a distance function), and aggregating the nearest groups ci and cj in a new one, thus obtaining n-1 clusters;

- new distances among groups are calculated and a new partition of the n-1 clusters is built up using the same procedure.

- the procedure is iterated untill all the n original objects are assembled in one unique cluster.

It is therefore clear that what makes the difference between alternative clustering methods is the way in which the distance between clusters is defined, or, more precisely, the way in which the new centroid of a merged cluster is calculated: this will vary with the desired clusters' characteristics. The median method - the algorithm we used - determines:

$d(ci,cj,c_k) = 0{,}5d(ci,ck)+0{,}5d(cj,ck)-0{,}25d(ci,cj)$,

where d(ci cj,ck) is the distance between cluster ck and the cluster obtained by merging clusters ci cj's.

Two are the main caracteristics of this method: first, the two combined clusters are equally weighted in the centroid computation, regardless of the number of cases in each i.e. this method is robust; second it should not suffer from 'chain effects' i.e. progressive agglomerations of objects which are not homogeneous with regard to one principal component.

An important problem was then deciding how many clusters to choose, since hierarchical methods (as the median one) provide many alternatives (from n to 0 groups); this was done by cutting the dendrogram (the 'tree' which describes the grouping dynamics) above the low aggregations (which bring together the elements that are very close to each other), and under the high aggregations, which lump together all the groups in the population.

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