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PRODUCTIVE EFFICIENCY IN THE IVORIAN MANUFACTURING SECTOR: AN EXPLORATORY STUDY USING A DATA ENVELOPMENT ANALYSIS APPROACH

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The African industrial structure is characterized by firm-size heterogeneity with the coexistence of small, if not micro, enterprises in the informal sector and large formal organizations operating with modern technology. In this paper, using the Data Envelopment Analysis production frontier methodology, we investigate the technical efficiency of Ivorian manufacturing firms in four sectors of economic activity: textiles and garments, metal products, food processing, and wood and furniture. Efficiency scores are adjusted to take into account the impact of the external operating environment. These scores are then broken down into three elements: the purely managerial effect, the impact of the scale of production, and a technological effect capturing the potential gain that could result from the adoption of modern technology by small informal organizations. Not only formal activities prove to be more efficient in scaling their production but also, they greatly benefit from their modern technology.

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JEL classification: D21, D24, L23, L25, O12

I. INTRODUCTION

In the analysis of the manufacturing sector of low-income countries, the relationship between firm size and productive efficiency has been and still remains a debatable issue. To some extent small size is more appropriate in an environment where firms face the likelihood of severe market and government failures.

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Direct participation of the owner in productive activities implies less sensitivity to the dimension of information, and lowers agency costs compared to large formal firms, where delegation gives rise to issues of potential adverse selection and moral hazard. The perspective of the theoreticians of property rights and agency relationships then applies. The manager being the "residual claimant" has a natural incentive to be a profit maximizer, and can help to promote loyalty as well as assisting in the emergence of efficient social conventions and behavioral norms (Schotter 1981; Leibenstein 1989). The operating environment can also be a relevant element in assuming a relative advantage possessed by small organizations, especially when these organizations benefit from an informal status. In such cases, they face few institutional restrictions in adjusting inputs in accordance with their productive needs, while for social reasons, most big firms bear acute public constraints on doing so.

If these arguments suggest that small informal enterprises can develop a highly productive performance, the opposite view can also be considered insofar as large modern firms more easily manage economic imperfections. In other words, bureaucratic costs are only one side of the coin. Size and governance structure are finally shaped by profit goals and the possibility for large firms to enjoy efficient human specialization as well as scale economies (Coase 1937; Williamson 1985). Moreover, labor turnover being lower in large companies, individuals can acquire some firm-specific skills allowing the creation of a core competence. The collective learning of the organization then accrues and facilitates higher productivity through a better coordination of production skills that contributes to long-run cooperation, and the integration of multiple streams of technologies.

On the basis of these analytical arguments, no clear-cut conclusion seems to emerge. This paper intends to undertake an empirical reappraisal of this debate by analyzing the productive efficiency of a representative sample of Ivorian manufacturing firms. Empirical indicators are calculated by mathematical programming models derived from the Data Envelopment Analysis (DEA) technique. The data set is provided by the Regional Program on Enterprise Development (RPED), an in-depth survey conducted by the World Bank of the manufacturing sectors of six sub-Saharan African countries (Burundi, Cameroon, Côte d'Ivoire, Kenya, Zambia, and Zimbabwe) between 1995 and 1996. In this paper, we refer only to the Ivorian database.

Section II presents the random sample that was drawn from four Ivorian manufacturing sectors offering a representative coverage of formal as well as informal enterprises: textile and garments, metal products, wood and furniture, and food processing. Section III describes the nonparametric frontier method that underlies our technical efficiency measurements. Two amendments to the classical DEA program are proposed. First, following the method used by Fried, Schmidt, and Yaisawarng (1999), efficiency scores are adjusted for the average impact of exogenous variables that capture the role of the economic and institutional operating environment. Second, we propose a breakdown of efficiency scores into three elements: managerial, scale, and technological effects. The latter allows an appraisal of the productive performance that the informal sector would achieve by adopting the more efficient technology of the formal sector. Section IV comments on the empirical results, while Section V provides a summary of our findings and discusses perspectives for further research.

II. THE SAMPLE OF THE IVORIAN MANUFACTURING FIRMS

The Ivorian manufacturing sector is one of the largest in sub-Saharan Africa. In 1995 and 1996, when the survey was conducted, this sector represented 25 percent of local GDP. Data collection was carried out under the supervision of the World Bank within the framework of RPED.[1] The main objective of the survey was to increase our knowledge concerning the creation process of African manufacturing firms and to shed some light on the problems they encounter in their local development. We also aimed to investigate the influence of institutional status, some organizations being formal while others are informal. In the international program (RPED) we refer to, formal firms are those recorded on the trade register. They are known to the government tax authorities and are potential taxpayers for all regular taxes resulting from their commercial activities. Informal enterprises are unregistered and avoid state corporate income taxes and social security contributions, with the exception of a trade tax paid to the district where they are located (for example, the "patentee").

Information about the 230 surveyed firms is given in Table I, where all but the "number of firms" figures are in percentages. The random sample of 230 firms was drawn from a total of 620 firms belonging to both formal and informal sectors. The Ivorian sampling procedure combines the stratification of the total population employed in the four sectors being studied. A probability mechanism is used for the selection of surveyed elements. The stratification is carried out using three characteristics: the sector-based activity (textile and garments, metal products, wood and furniture, and food processing), the institutional status of organizations (formal, informal), and the geographical location of firms (the three main cities of Abidjan, Bouaké, San Pedro and other urban areas). Using this stratification, a representative sample is drawn, giving each element in the population the same probability of being selected through a lottery process.

Table I highlights the relationships between the size of productive organizations and the sector of operation. Most micro-enterprises are in textile and garments (65%),

[1] Several papers have been published from the RPED surveys. Among the more recent ones are the papers by Bigsten, Isaksson, et al. (2000), and Bigsten, Collier, Dercon, Gauthier, Gunning, et al. (1999), Bigsten, Collier, Dercon, Gauthier, Isaksson, et al. (2000), and Chapelle and Plane (2005). The surveys were carried out over the period 1993–95 for all the countries, with the exception of Ghana (1992–94) and Côte d'Ivoire (1995–96).

TABLE I

STATISTICAL DISTRIBUTION: FIRMS ACCORDING TO SIZE AND SECTOR

(%)

	Sector of Operation and Size of Organizations				Total
	Food Processing	Textile and Garments	Wood and Furniture	Metal Products	
Number of firms	58	57	60	55	230
Micro	1 (2)	65 (61)	27 (42)	7 (18)	100
Small	22 (54)	34 (35)	23 (39)	21 (60)	100
Medium	37 (12)	11 (1)	19 (4)	33 (13)	100
Large	46 (32)	12 (3)	31 (15)	11 (9)	100
Total	(100)	(100)	(100)	(100)	

Source: Authors' calculation from the data base of Côte d'Ivoire in the RPED, World Bank.

TABLE II

MAIN PRODUCTION CHARACTERISTICS OF IVORIAN FIRMS BY INSTITUTIONAL STATUS
(Sample averages in 1995)

		Formal Firms		Informal Firms		All Firms	
(1)	Number of firms	129	(100.0)	57	(100.0)	186	(100.0)
	Micro (less than 5 workers)	2	(1.6)	19	(33.3)	21	(11.3)
	Small (5 to 49)	66	(51.2)	37	(64.9)	103	(55.4)
	Medium (50 to 99)	20	(15.5)	1	(1.8)	21	(11.3)
	Large (100 and more)	41	(31.7)	0	(0.0)	41	(22.0)
(2)	Value added (*Q*) (1,000 CFA francs)	1,881,860		12,000		79,321	
(3)	Capital stock (*K*) (1,000 CFA francs)	542,370		1,980		18,440	
(4)	Workforce (*L*) (No. of workers)	179.9		6.6		79.6	
(5)	Human capital (*H*) (No. of school years[a])	5.20		5.13		5.16	
(6)	Q/K	3.46		6.10		4.30	

Source: Same as Table I.
Notes: 1. Figures in parentheses are percentages.
2. Figures of (2), (3), (4), and (5) refer to firm average values over the sample.
[a] Calculated for the representative agent of the firm.

to a lesser extent in wood and furniture (27%), while few of them are found in the metal products (7%) and food processing (1%) sectors. The columns of the table give additional insights. The figures in parentheses show that while large organizations are far from prevalent, their share is not negligible in the food and processing sector (32%). Their contribution is however limited to 3% for textile and garments manufacturing.

Table II summarizes the main characteristics of the 186 firms that constitute the restricted sample on which the empirical work is based. The difference with the initial sample (230 enterprises) proceeds from a lack of information as regards primary inputs for the calculation of productivity measurement, or the adjustment of performance for the impact of the operating environment (see Section III). The table illustrates the contrast between formal and informal status. The list of taxpayers to the central administration (formal sector) and the list of local taxpayers to municipal corporations (for example, "patentee" for informal enterprises) were combined to constitute the total sampling population. Within the four sectors, formal firms have a higher capital-labor ratio, and are significantly larger than informal ones, no matter what the criterion (for example, value added, capital stock, or workforce).

III. NONPARAMETRIC MEASUREMENT OF TECHNICAL EFFICIENCY: FORMAL PROCEDURE

A. *Parametric versus Nonparametric Frontier Methods*

The calculation of a production frontier and resulting technical efficiency scores can be carried out either by econometric or by mathematical programming approaches. Each of these two methods has its own supporters and detractors. While Lovell (1993) argues that "neither approach strictly dominates the other," Coelli, Rao, and Battese (1998) suggest that "the selection of the appropriate method should be made on a pragmatic basis." This last position has been adopted in this paper where technical efficiency is measured by the Data Envelopment Analysis (DEA) technique.

When cross-sectional econometric regressions are considered, the stochastic model relies on relatively limited information to separate the random error term in the normal disturbance and the inefficiency component (Lovell 1993). The DEA technique does not require hypotheses about the distribution of the error term. These arguments are valuable in the context of an empirical analysis where little is known about productive technology and profit behavior of formal and informal enterprises. Moreover, with the stochastic approach, there is a risk of confusion between the misspecification effect of the functional form and the technical efficiency measure.[2]

The programming approach is not sensitive to this problem. But this is only a relative advantage, as its deterministic nature mixes up technical inefficiency and

[2] Focusing on panel data estimators of technical efficiency, the Monte Carlo study of Gong and Sickles (1992) compared several stochastic parametric frontier estimators and a basic DEA model with strong disposability and variable returns to scale. Their findings indicate that the former methods outperform the latter only when the chosen functional form is close to the underlying technology and when there is little correlation between the regressors and the technical inefficiency term.

random noise. Any deviation from the frontier is regarded as inefficiency, giving rise to a particular sensitivity to *outliers* (Cornwell and Schmidt 1996). However, in contrast to parametric analysis, where it is assumed that the single optimized regression equation applies to each empirical observation, the DEA method calculates the performance of each Decision-Making Unit with regard to a specific peer group reflecting the *best practice* for the observation (Seiford 1996). An outlier demonstrating a poor technical performance does not influence the efficiency score of other units. Indeed, it does not contribute to the definition of the frontier (e.g., the conical hull) as is the case in the parametric frontier model. An outlier with an "artificially" high productive performance is potentially more disturbing. However, its influence as a peer can be locally restrained with a convexity restriction that limits benchmarking within a subsample of firms. For example, when calculating the DEA frontier under the assumption of variable returns to scale (DEA-VRS), we presume that this frontier is defined as a convex hull of intersecting planes enveloping the data set. Therefore a firm cannot be benchmarked against *peers* that are substantially larger or smaller than itself.[3]

The choice of the DEA technique, and especially the "four-stage" procedure that we describe below, is also motivated by our objective when calculating technical efficiency scores. As the institutional and macroeconomic environments are likely to vary across firms, performance should be evaluated both "gross" and "net" of exogenous effects. If the stochastic frontier model can be used to estimate inefficiency scores incorporating an explicit function of a vector of environmental characteristics, efficiency predictions are "gross" measurements (Battese and Coelli 1995).[4] Transformation into "net" measurements (e.g., adjusted for the impact of exogenous factors) requires all firms to be placed in an identical operating environment, and the residuals being given, the expression for the conditional expectation of the technical efficiency term must be recalculated (Coelli, Perelman, and Elliot 1999).[5] Finally, the parametric frontier provides radial scores while the DEA program allows taking into account the effect of exogenous factors on the non-radial input slack. That is, while in a parametric approach the environmental factors can

[3] This paper adheres to the traditional conception that DEA methods are deterministic. However, recent developments (e.g., Simar and Wilson 2000, 2001) have established that these nonparametric frontier estimators have small convergence rates, but that their small sampling error can be improved upon, either by using information on its asymptotic distribution of efficiency estimates (if available), or by simulated (bootstrapped) empirical distributions. Since these methods are highly computer-intensive and have not been extended to accommodate the four-stage model adopted in this paper (see below), we refrain from any further discussion but refer the reader to relevant literature.

[4] Four computer programs are generally used: SHAZAM, DEAP, FRONTIER, and LIMDEP. In this paper we use DEAP for the calculation of the technical efficiency scores, and STATA for the econometric estimation.

[5] Though this conversion from "gross" to "net" measures is possible, due to the maximum likelihood estimation it is not easy to operate.

only affect the distance to the frontier, the DEA-based "four-stage" procedure in principle allows these environmental characteristics to influence the shape of the production frontier. The latter hypothesis allowing for a non-neutral change in the frontier is undoubtedly the most general.

B. *The Operating Environment and the Four-Stage Calculation Procedure*

In attempting to explain the heterogeneous structure of the manufacturing sector, attention must be focused on the complexity of the factors contributing to productive performance. To investigate their respective role, we adopt the four-stage procedure, introduced by Fried, Schmidt, and Yaisawarng (1999).

First, the classical nonparametric DEA frontier is calculated to obtain a distribution of efficiency scores. These scores refer to the radial measurement of technical efficiency as defined by Farrell (1957). In conformity with a fair number of studies, the input-oriented model is preferred to the output-oriented DEA program. Indeed, the input quantities appear to be the primary decision variables, as managers have a better control over them than they have over outputs. This is especially true for large modern firms benefiting from trade protection. Stimulating local demand is not easy when firms are rarely competitive enough to export a potential surplus. In the second stage, an econometric regression analysis is performed to correct the input use from effects beyond the control of managers. To carry out this exercise for an input-oriented model, the sum of the radial movement and the non-radial input slack is econometrically regressed on a vector of variables reflecting the average impact of exogenous factors.[6] In the third stage, the regression parameters are used to assess the virtual consumption of inputs that would be observed if all Ivorian firms evolved under similar operating conditions. In the final fourth stage, adjusted primary inputs are used to rerun four DEA frontiers (one for each manufacturing sector) with efficiency scores revealing a more appropriate measurement of intrinsic managerial abilities.

The first stage refers to the DEA mathematical programming model as defined by Banker, Charnes, and Cooper (1984). This model makes it possible to control for economic inefficiency originating from production with variable returns to scale (VRS). Company performance can therefore be broken down into "pure technical" or managerial and "scale" inefficiencies. As African manufacturing firms operate in an environment of imperfect competition, with various financial and regulatory constraints, not all of firms necessarily operate at an optimum scale.

The input distance function introduced by Shephard (1970) characterizes production technology by considering a minimum proportion contraction of the input vector given an output vector. The production technology denotes the set of all

[6] Koopmans (1951) defines technical inefficiency in terms of the radial reduction in inputs that is possible, but also in terms of input or output slacks. See Coelli, Rao, and Battese (1998) or Fried et al. (1999).

input vectors (x), which can produce the output vectors (q). Q is a matrix of outputs and X a matrix of inputs (I). The possibility of accounting for a sub-optimal scale is obtained by the convexity constraint ($\lambda I = 1$) where I is a vector of ones and λ a vector of positive weights which allow the formation of the technology. The assumption of VRS ensures that an inefficient firm is only benchmarked against firms of a similar size.

$$L(q) = \{x\colon \lambda Q \geq q,\ \lambda X \leq x,\ \lambda I = 1,\ \lambda \in R_+^i\}. \tag{1}$$

Given the piecewise linear input requirement set to account for variable returns to scale $L(q)$, the DEA model is derived from the linear programming problem as defined below where θ^i is a scalar value representing the *proportional contraction* of all inputs (j) for ith firm, holding input ratios and output level constant. This measure underlies efficiency scores and neglects the non-radial input slack, which represents the possibility of maintaining output while contracting the volume of at least one input, the others being held constant.

$$\begin{aligned}
&\min_{\theta,\lambda} \theta^i \\
&\text{s}\cdot\text{t} \quad \lambda Q \geq q^i, \\
&\qquad \lambda X \leq \theta x^i \qquad i = 1, \ldots, n \text{ (firms)}, \\
&\qquad \lambda I = 1 \qquad\quad\ j = 1, \ldots, k \text{ (inputs)}, \\
&\qquad \lambda \in R_+^i.
\end{aligned}$$

In adjusting the technical inefficiency of firms for factors outside managerial control, we choose tobit regressions to account for the unilateral distribution of the dependent variable. Following the Fried, Schmidt, and Yaisawarng (1999) notation, the excessive use of the jth input that we denote by ITS_j^i, results in two components: radial movement, or the technical inefficiency, as initially measured by Farrell (1957) and non-radial movement, or the "slack," which is generally neglected, but considered by Koopmans (1951) in his strict definition of technical efficiency.[7] ITS_j^i have been regressed on the appropriate vector of economic and institutional factors (Z_j^i). The highest predicted value of the econometric relation ($\text{Max}^i\, ITS_j^i$) highlights the overall effect of these factors for the firm having the least favorable set of operating conditions. Effective quantities of the jth primary input are then adjusted to place all productive firms in this environment (equation 2).

$$\begin{cases}
ITS_j^i = f_j(Z_j^i \cdot \hat{\beta}_j) & j = 1, 2, 3 \text{ (inputs)}, \\
\text{with} & \\
ITS_j^i = f_j(Z_j^i \cdot \beta_j \cdot U_j^i) & i = 1, \ldots, 186 \text{ (firms)},
\end{cases}$$

$$x_j^{iadj} = x_j^i + [\text{Max}^i\, ITS_j^i - ITS_j^i]. \tag{2}$$

[7] An illustration of the two components is provided in the Appendix.

$\text{Max}^i ITS^i_j = ITS^i_j$ stands for the organization with the worst environment. A positive difference is observed for all other organizations where the same output can be obtained with a lower use of inputs. This method has been applied three times under the hypothesis that the operating environment differs across the three inputs. On the basis of these new virtual volumes of inputs, the DEA model can be recomputed in the fourth stage in order to obtain what we call a "pure" technical or managerial efficiency.

C. *Measurement of a Technological Efficiency Differential*

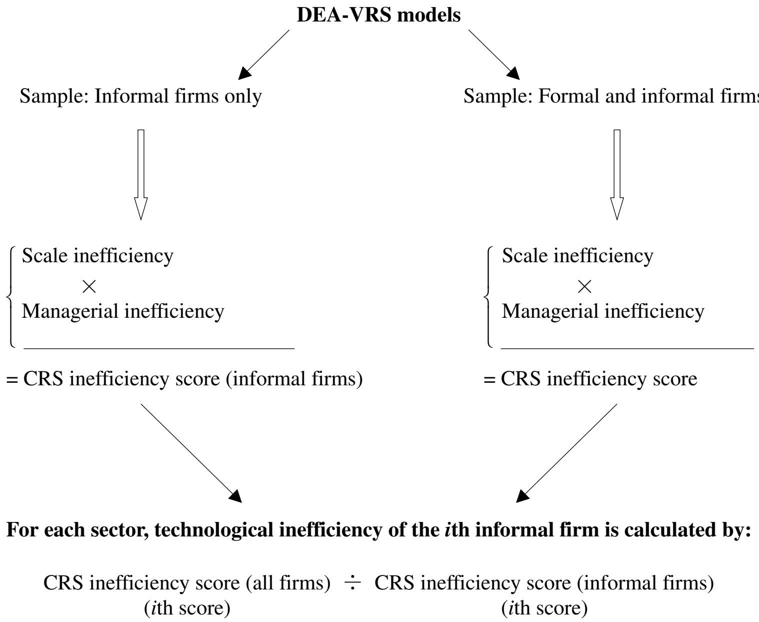
To account for the heterogeneity of the surveyed firms, an additional hypothesis has been introduced into the measurement of efficiency scores and their component effects. The binary breakdown of scores into scale and technical or managerial inefficiency would be misleading if all organizations did not refer to the same technology. Accordingly, a third component has to be incorporated to reflect the systematic technological difference between sub-groups of productive organizations. To divide the population into homogenous sub-groups, several criteria are potentially available such as the capital-labor ratio or the firm size as represented by total employment. Both have the disadvantage of being conditional on a threshold value for the stratification to be operational. As all the surveyed entrepreneurs were asked to declare by themselves their adherence to the formal or the informal sector (*FORM*), this direct information can also be used.

In what amounts to a large body of literature, small informal enterprises have traditionally been considered as transitory organizations contributing towards poverty reduction through a labor-intensive technology that increases the demand for unskilled labor. As Killick (1981) emphasizes, lower-paying informal activities do at least offer some kind of living until a modern sector job comes along. Therefore, small informal organizations do not enjoy the dynamic perspective of long-run profit maximization, and are unlikely to employ an efficient technology combining labor and capital inputs in the right proportions. Following this argument, informal enterprises are doomed to either reach the formal sector or perish.[8]

Assuming that formal firms have the appropriate technology, efficiency scores can be calculated easily. The DEA-VRS model facilitates the breakdown into managerial and scale inefficiency factors. For informal enterprises, efficiency scores comprise three components. Two of them are obtained by calculating the DEA-VRS model restricted to the subsample of informal firms. The third reflects the technological gap for each firm as measured by the distance between the two Constant Returns to Scale frontiers. The complete procedure is displayed in Figures 1 and 2.

[8] This argument might be qualified. Influential empirical works in terms of econometric duration models have shown that the flexibility of informal enterprises can be a survival factor over a long period.

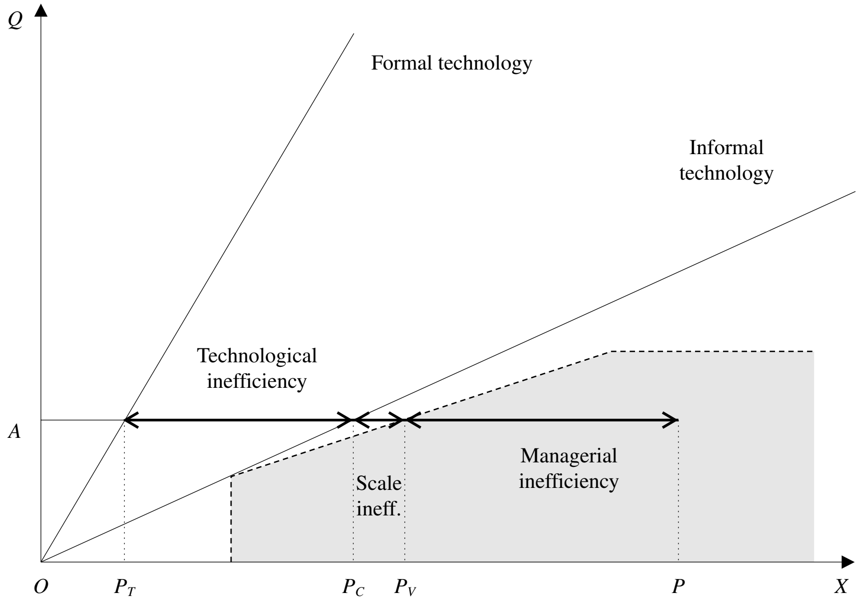
Fig. 1. Technical Inefficiency and Its Components
(A sector-based measurement using DEA)



[a] From a sector-based sample we calculate scale and technical or managerial inefficiencies of formal firms. The determination of the technological distance between formal and informal enterprises is calculated by dividing scores of the *i*th firm under the two CRS models. A similar exercise has been conducted for each of the four sectors.

In Figure 2, one of the four sectoral samples has been divided according to institutional status. A first DEA program has been solved by projecting all enterprises on to the common "best frontier," which is wholly determined by the technical efficiency of formal firms. Under this frontier, and for the formal firms only, the variable returns-to-scale model allows the decomposition of scores into managerial and scale efficiency. A similar approach has been adopted in a second stage with a DEA analysis restricted to informal enterprises. For each of these organizations, scale and managerial technical efficiency are derived from this frontier while difference between the efficiency scores under the formal and informal frontiers determines what we call the "technological efficiency." Consequently, an informal enterprise operating with a combination (AP) faces three sources of input-oriented technical efficiency that we express in ratio form. Managerial inefficiency is evaluated by AP_V/AP and scale inefficiency by AP_C/AP_V. The difference between the informal and formal constant returns to scale frontiers, AP_T/AP_C, captures the hypothetical advantage that an informal firm would gain by adopting the more effi-

Fig. 2. Components of Firm Technical Inefficiency
(Input-Oriented Model)



$$\underbrace{\frac{AP_T}{AP}}_{\text{Technical inefficiency}} = \underbrace{\frac{AP_T}{AP_C}}_{\text{Technological inefficiency}} \times \underbrace{\frac{AP_V}{AP}}_{\text{Managerial inefficiency}} \times \underbrace{\frac{AP_C}{AP_V}}_{\text{Scale inefficiency}}$$

Note: Two sources of technical inefficiency are retained for formal firms, and three for informal ones. For a more convenient reading of the figure, let us say that the P, P_T, P_V, P_C on the axis (OX) refer to different levels of an input X for the production of output A.

cient technology of the modern sector.[9] This approach is quite close to more standard alternative methods in which "environment variables" are used in the DEA program to restrict the comparison set (Charnes, Cooper, and Rhodes 1981; Charnes et al. 1994).[10]

[9] We assume that formal firms have only two potential sources of technical inefficiency: one resulting from management and the other proceeding from the production scale. In Figure 2, the VRS-DEA model of formal firms is not represented. The illustrative example refers only to the case of an informal firm.

[10] One can also refer to Coelli, Rao, and Battese (1998, pp. 166–72) or Cooper, Seiford, and Tone (2000, Chap. 7).

IV. NONPARAMETRIC MEASUREMENTS OF EFFICIENCY SCORES: THE EMPIRICAL ANALYSIS

A. *Production Technology Variables*

The same methodological approach has been adopted for the four manufacturing sectors. To estimate the sectoral capital stock at constant market prices, the perpetual-inventory method was used. As the organizations were not asked to produce balance sheets, (and in fact, firms in the informal sector are unable to provide one) capital stock, in CFA francs, was evaluated by combining data relating to initial equipment and the value of registered investments over the period 1984–93. Since figures by type of assets, or even in global terms, are not available, an annual depreciation of the capital stock of 4.5 percent has been assumed. This percentage corresponds to a mean asset life of 22 years. Labor input was measured by categorizing workers using the number of hours multiplied by the relative weight of the category within the workforce of the firm. This calculation applies to both temporary and permanent employees, the mix of which tends to vary across firms. In addition, a third input was taken into account to capture the specific impact of human qualifications. Instead of distinguishing between skilled and unskilled workers, a variable reflecting the specific human capital of the firm has been calculated. For each worker category, the average number of school years was considered for what is termed in the questionnaire a "representative" agent. A weighted average of these statistics serves as a proxy for the human capital of the organization.

B. *Operating Environment Variables*

To adjust input quantities for exogenous features of the environment, variables affecting the relative importance of transaction costs have also been considered. Official regulation (*REG* in Table IV) and corruption (*COR*) do not have the same impact on different firms. The deleterious impact of these factors is potentially larger for modern firms. Qualitative variables were defined on the basis of the answers from surveyed managers concerning the excess unit cost resulting from this institutional context. In both cases, the increasing disturbance was measured by a discrete variable with a value ranging from 1 to 5. Trade unions (*UNION*) may also have a significant impact. They play an active role in internal negotiations and potentially contribute to the way the economic surplus of the organization is distributed. Unions can help the emergence of procedural arrangements that encourage effort and loyalty. But they also restrict the set of managerial decisions by reducing the speed of adjustment of the labor force to the level required by the current output.

Additional variables have also been tested. One is a binary variable that distinguishes firms with an official registration from others (*FORM*). This distinction makes it possible to capture a wide range of unobservable exogenous effects. The second variable is designed to test the economic cost resulting from public restrictions relating to the localization of investments (*LOC*). Managers were asked to evaluate the intensity of government restrictions underlying the localization of investment and its impact on the growth of activity using a ranking of one (no obstacle) to five (severe restrictions). Following the same procedure, a qualitative explanatory variable, scaling answers from 1 to 5, was used to test the potential effect of a poor public infrastructure (*INFRA*). As highlighted by Kerf and Smith (1996), no other region in the world is in greater need of new investments and more efficient infrastructures than sub-Saharan Africa. Although transportation costs and inadequate supply of electricity or telecommunication services may be a handicap to small enterprises, large capitalistic firms are potentially more severely affected by this problem as inefficient public utilities increase economic uncertainty and restrict the use of productive capacities (Plane 1999).

Some variables have also been included to evaluate the difficulty that firms encounter in obtaining institutional credit. Small and micro-enterprises are generally considered to be handicapped by risk-averse commercial banks and by the high transaction costs resulting from negotiation and supervision of small loans. This effect was tested by means of a dummy variable that combines information about managers who applied for a loan but failed to get it, and those who, anticipating a rejection, did not apply to any commercial bank (*LOAN*). This financial constraint reflects capital market imperfections and tends to increase the age of the capital equipment (*AGE*) of small enterprises. When capital asset prices fail to reflect fully the productivity differential embodied in successive generations of capital equipment, Page (1984) argues that smaller firms may appear inefficient relative to a single cross-sectional frontier defined by firms with newer capital equipment.[11]

C. *Efficiency Scores and Their Breakdown: Results and Comments*

Before discussing efficiency scores, corrected or not for the impact of the operating environment, let us briefly comment on the results of the tobit regressions shown in Table III. Most of the variables display the expected sign with statistically significant coefficients. Due to potential input substitution among primary inputs, the tobit models have been estimated by using the same vector of dependent variables,

[11] An exogeneity test about *LOAN* and *AGE* was implemented using Hausman's (1978) test procedure. An additional reference is Wu (1973). First, for each observed *LOAN* and *AGE* variable, a reduced-form regression was estimated using the probit and the tobit model, respectively. Second, the observed variable and its predicted value were tested jointly by regressing them on the total input slack (*ITS*) of the capital stock. The log likelihood of the regression allows us to test the explanatory power of the variable for which endogeneity is suspected. For *LOAN* and *AGE*, exogeneity was not rejected.

TABLE III

SECTOR-BASED TOBIT REGRESSIONS: PRIMARY INPUTS ADJUSTMENT FOR THE EXOGENOUS ENVIRONMENT

	Food Processing			Textile and Garments			Wood and Furniture			Metal Products		
	Labor	Technical Capital	Human Capital	Labor	Technical Capital	Human Capital	Labor	Technical Capital	Human Capital	Labor	Technical Capital	Human Capital
UNION	139	3,275	−1.29	255	6,521	−3.7	39	2,713	−0.9	102	2,516	−6.13
	(3.39)***	(0.75)	(0.24)	(4.12)***	(1.49)	(− 0.8)	(1.16)	(1.05)	(− 0.9)	(3.13)***	(0.36)	(−1.71)*
REG	31	1,253	12	68	1,275	27	16	2,106	−16	14	3,164	7.6
	(1.53)	(0.58)	(1.14)	(1.70)*	(1.04)	(1.58)	(1.12)	(1.14)	(−1.07)	(1.09)	(1.21)	(1.58)
COR	128	25,273	41	54	2,751	34	75	24,312	32	98	78,772	−1.18
	(2.16)**	(2.75)***	(0.91)	(1.34)	(0.91)	(0.35)	(1.54)	(2.98)***	(0.28)	(1.59)	(3.19)***	(−1.24)
LOAN	138	29,758	251	159	3,157	189	124	416	168	320	−25.95	−3.2
	(0.08)	(1.05)	(0.38)	(0.37)	(0.35)	(1.06)	(0.70)	(0.00)	(0.33)	(0.37)	(−1.28)	(−0.08)
LOC	38	−15,927	4.3	59	1,624	7.6	127	618	2.7	354	10,612	−2.5
	(0.95)	(−2.39)**	(1.78)*	(1.34)	(1.98)**	(1.75)*	(2.58)**	(0.28)	(0.85)	(4.16)***	(1.95)*	(−0.73)
INFRA	201	27,357	21.1	122	227,149	16.2	158	129,762	31	317	−2,634	−2.9
	(0.60)	(1.12)	(0.06)	(0.28)	(2.27)**	(0.00)	(0.45)	(1.80)*	(0.28)	(0.88)	(−0.28)	(0.00)
FORM	29	65,829	5.8	16	2,575	3.2	33	19,756	12	14	36,791	25
	(0.08)	(1.73)*	(4.45)***	(0.00)	(0.45)	(2.75)**	(0.51)	(1.48)	(0.00)	(0.08)	(2.26)**	(0.33)
AGE	0.9	10,753	1.12	2.53	2,653	2.2	1.7	2,864	0.72	3.1	2,179	1.7
	(0.35)	(2.80)***	(0.30)	(1.73)*	(1.28)	(0.50)	(1.36)	(1.37)	(0.00)	(2.09)**	(1.39)	(0.34)
INTERCEPT	62	−193,512	10.9	−78	2,174	−10.9	−29	2,643	264	36	265,432	26
	(2.27)**	(−2.95)***	(0.20)	(−2.59)***	(1.14)	(−0.50)	(−1.50)	(1.29)	(0.58)	(0.38)	(3.51)***	(0.00)
Log likelihood	−2,904	−1,579	−216	−1,275	−3,127	−196	−3,951	−2,605	−1,270	−876	−1,152	−865

Note: Dependent variables are the total radial plus non-radial slacks. The Student's *t*-tests are given under the coefficient with the following levels of confidence: 99% (***), 95% (**), and 90% (*).

TABLE

SECTOR-BASED TECHNICAL EFFICIENCY SCORES:

	Food Processing				Textile and Garments			
	F (37)	I (10)	Total (47)	W-Test	F (28)	I (18)	Total (46)	W-Test
Not adjusted for environment:								
Total	0.54	0.34	0.42	***	0.44	0.20	0.32	***
	(0.38)	(0.20)	(0.29)		(0.38)	(0.22)	(0.29)	
Technological	1.00	0.53	0.70		1.00	0.41	0.73	
		(0.25)	(0.33)			(0.35)	(0.42)	
Managerial	0.65	0.78	0.73	***	0.58	0.69	0.61	***
	(0.41)	(0.52)	(0.51)		(0.36)	(0.41)	(0.50)	
Scale	0.83	0.82	0.82	ns	0.76	0.68	0.72	**
	(0.49)	(0.52)	(0.51)		(0.32)	(0.41)	(0.39)	
Adjusted for environment:								
Total	0.58	0.35	0.44	***	0.47	0.21	0.33	***
	(0.29)	(0.18)	(0.25)		(0.36)	(0.16)	(0.28)	
Technological	1.00	0.55	0.72		1.00	0.43	0.70	
		(0.31)	(0.53)			(0.25)	(0.34)	
Managerial	0.70	0.79	0.75	***	0.63	0.68	0.65	**
	(0.40)	(0.39)	(0.45)		(0.35)	(0.42)	(0.48)	
Scale	0.83	0.81	0.82	ns	0.75	0.70	0.73	**
	(0.52)	(0.47)	(0.49)		(0.39)	(0.16)	(0.30)	

Notes: 1. F = formal, I = informal, and W-test = Wilcoxon test.
2. The differences between the distributions is tested with the following levels of
3. The number of observations and the standard deviations are given in parentheses.

no matter what their respective statistical relevance may be. Although the cross-sectional dimension of the sample means that it is unlikely to control for all the relevant variables over all four sectors, it is clear that some conditions beyond the control of plant managers exert a significant influence on technical efficiency performance. Across the four sectors, the hypothesis that the operating environment imposes a severe constraint on the way firms are managed is generally evidenced for labor input through the positive correlation between the excess use of this factor and *UNION* and *COR*, to a lesser extent *REG*.

With regard to the other primary inputs, the sensitivity of capital equipment with respect to *LOC,* to the quality of infrastructure (*INFRA*) or the age of capital (*AGE*) is not statistically rejected. In addition, except for the textile and garments category, the formal sector (*FORM*) tends to be a source of an excess use of both technical and human capital. This result reflects the specific short-run exogenous constraints that the modern sector faces. A more capital-intensive technology, which goes along with a formal status, is a source of specific rigidities. For two of the four sectors the

IV

ADJUSTED OR NOT FOR THE OPERATING ENVIRONMENT

Wood and Furniture				Metal Products			
F (36)	I (13)	Total (49)	W-Test	F (28)	I (16)	Total (44)	W-Test
0.47	0.39	0.44	**	0.40	0.28	0.34	***
(0.31)	(0.41)	(0.40)		(0.42)	(0.23)	(0.40)	
1.00	0.73	0.72		1.00	0.67	0.69	
	(0.53)	(0.72)			(0.53)	(0.59)	
0.68	0.85	0.70	**	0.72	0.83	0.78	***
(0.41)	(0.52)	(0.45)		(0.48)	(0.69)	(0.59)	
0.69	0.63	0.86	**	0.56	0.50	0.63	**
(0.58)	(0.71)	(0.76)		(0.42)	(0.48)	(0.51)	
0.50	0.40	0.45	**	0.42	0.28	0.37	***
(0.29)	(0.28)	(0.32)		(0.35)	(0.27)	(0.30)	
1.00	0.74	0.73		1.00	0.66	0.72	
	(0.46)	(0.63)			(0.42)	(0.58)	
0.70	0.86	0.75	**	0.78	0.85	0.84	**
(0.36)	(0.57)	(0.49)		(0.51)	(0.62)	(0.53)	
0.72	0.63	0.82	**	0.54	0.50	0.61	**
(0.60)	(0.59)	(0.63)		(0.40)	(0.48)	(0.46)	

confidence: 99% (***), 95% (**), and 90% (*); ns = non-significant.

same result is checked for the skilled workforce. Actual and desired levels of these two variables can therefore diverge, suggesting that the capital stock or the number of skilled workers can be larger than the optimal level would require.

In order to place all firms within the least favorable set of exogenous conditions observed within samples, the estimated parameters of tobit regressions were used to recompute the DEA efficiency scores with new pseudo data sets where inputs are adjusted for the influence of exogenous conditions. Table IV allows us to assess the impact of our corrections through a twofold breakdown.

For any given sector, the first breakdown helps to evaluate the difference between scores of both formal and informal averages. The second breakdown sheds some light on the respective contributions of managerial, scale, and technological effects. Under each distribution, the standard deviation is given in parentheses. In the last-sector-based column of Table IV, on the right-hand side, the results of the nonparametric Wilcoxon test highlight the difference between formal and informal distributions. Corrections for the operating environment, given in the lower part of the table, somewhat modify the results. Although the average performance of the informal sector is unaffected, the average performance of the formal sector improves.

The breakdown of technical efficiency scores into the three aforementioned elements is interesting in several respects. However, we must remember that the decomposition within both statuses is conditional on the assumption of a technological difference between formal and informal sectors. On the one hand, this hypothesis is not necessary for comparison of total average efficiency scores, as formal and informal enterprises refer to the same global frontier (Figure 2). On this basis, one can say that the productive performance of large formal firms predominates over that of small informal enterprises in the four sectors, though to a lesser degree in the wood and furniture sector. On the other hand, the aforementioned hypothesis is crucial when making direct comparisons, and this is what we do with respect to managerial or scale efficiency scores across the two institutional statuses. Keeping this restriction in mind, what can we say about Table IV?

First, managerial efficiency proves to be systematically higher within informal enterprises. For three sectors, the Wilcoxon test is statistically significant at the 99 percent level of confidence. When adjusting the scores for the impact of the exogenous environment, the gap between the two institutional statuses reduces, but the difference remains strongly to the advantage of informal activities. From these empirical results, and considering that the tobit models controlled for all of the relevant variables, some practical conclusions emerge. The impact of the external environment is not negligible. But, if small informal enterprises benefit from less regulatory obstacles, the arguments proceeding from the property rights and agency costs theories are not rejected. The adjustment for the exogenous environment does not alter the conclusion that small enterprises have a higher managerial efficiency than large organizations.

Second, and to some extent surprisingly, if small organizations outperform large ones in reducing pure managerial inefficiency, reported scores provide evidence, at a 95 percent level of confidence for three manufacturing sectors, that formal firms are more efficient in scaling their production. This empirical result, which remains good when scores are adjusted for the impact of the environment, conflicts somewhat with the current idea that a labor-intensive technology is less subject to indivisibility effects. In starting their business, small entrepreneurs might face fixed or sunk costs that prevent them from achieving cost-minimization. The relative importance of this cost is especially significant, as micro-enterprises are young and exposed to a higher exit rate. The procedural rationality underlying the decision-making process also has its own share of responsibility. Because of their limited knowledge and computational abilities, small operators often fail to determine the correct amount for their initial investment.

Finally, results show the large benefit of using the most efficient technology of the formal sector. This is a key element in explaining the average technical efficiency difference between subsamples. The need for small enterprises to move accordingly will especially depend on the strengthening of local competition with both national and foreign modern firms. The reduction of the Ivorian regulatory rules in itself calls for a changeover, as this reform tends to work in favor of large modern firms. International trade liberalization has a similar result and will strongly affect all Ivorian manufacturing activities. This will be the case in the textile and garments sector. In some sectors, for example wood and furniture manufacturing, the weight of the product may provide natural protection and accordingly an advantage for preserving the profitability of informal activities. But beyond the opportunity for technological change in accordance with stronger competition in the economic environment, the question arises whether such technology can be adopted and properly managed by Ivorian micro-entrepreneurs.

Indeed, the industrial skill of a firm can be considered as the sum of practical knowledge and know-how, manifested as a set of relevant habits that have become established as routine over time. It follows that trying to become fully efficient is an uncertain process. Changing capital and retraining the labor force induce significant costs before the process earns its full return. As Stiglitz (1989) remarked, a major difference between the developed and developing countries arises from learning by doing and the limits on the ability to transfer the learning across boundaries. According to the *missing middle* analysis, such transfers are no easier locally, between formal and informal organizations. The productive interest of modern technology is therefore hypothetical, especially if the objective of small enterprises consists of serving niche markets or specific segments of domestic demand.

V. CONCLUSION

We have investigated the technical efficiency of Ivorian firms by considering a random sample drawn from four sectors of manufacturing activity. To implement this exercise, the Data Envelopment Analysis (DEA) method was adopted with efficiency scores derived from the linear programming framework. Following a four-stage procedure, we have also calculated technical efficiency performance with primary inputs adjusted for the influence of exogenous economic and institutional conditions. Whichever DEA model we refer to, small informal enterprises have demonstrated a higher managerial performance compared to larger formal organizations. These empirical results support the view that some disadvantages occur with increasing size. They are connected to the external environment, but also to the organizational structure and the difficulties involved in managing incentive problems. However, "pure" managerial efficiency is only part of the story. Large and modern organizations benefit from a more efficient technology. In addition, and somewhat surprisingly, as they face more functional rigidities, they prove to be closer to the optimal production scale, possibly because they are less affected by constraints on finance and investment indivisibilities.

Although our results are interesting, more methodological work is needed in order to relax the restrictive assumptions concerning the calculation of efficiency scores and their components. The empirical hypothesis that all formal firms possess the appropriate technology while informal enterprises do not and would gain in adopting it has to be qualified. As Tybout (2000) remarks, if there is substantial uncertainty about future demand conditions, it may make sense to rely more heavily on labor-intensive technology. Moreover, it is reasonable to assume that few small entrepreneurs have the managerial "know-how" to manage such a radical change. While the choice of a modern technology would surely benefit those who are able to use it efficiently, such a change would be a risky venture for most producers who might additionally suffer from a potential loss in "pure" managerial efficiency. The more formal relations of modern firms are accompanied by more diluted responsibilities and less operational flexibility in the management of the external operating environment (Tybout 1996). Beyond this hypothetical interest concerning the "right" technology, the subsequent implication of deregulation and trade liberalization arises: in a more competitive environment, surviving firms will be those that succeed in combining the right technology and the right scale of production while achieving the best managerial efficiency.

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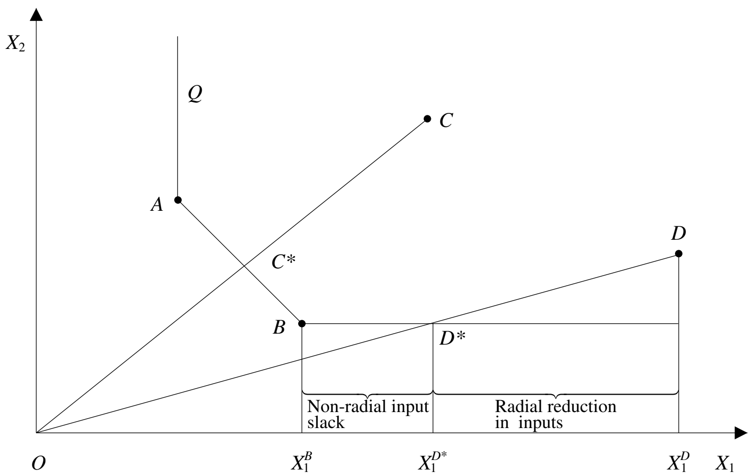
APPENDIX

In the following figure, four firms are considered: *A*, *B*, *C*, and *D*, which are supposed to use only two inputs, denoted by X_1, X_2 to produce the same output *Q*. While *A* and *B* are technically efficient, *C* and *D* are not. The radial movement is measured by OC^*/OC and OD^*/OD, respectively. When reaching the frontier, if C^* is fully efficient, D^* is not, as it is still possible to produce the same output with a lower quantity of input. This potential reduction in input X_1, which we measure through the difference between X_1^{D*} and X_1^B, is referred to as the non-radial slack in input X_1.

Illustration of the Concept of Radial and Non-radial Input Slack



Source: Fried, Schmidt, and Yaisawarng (1999).