Age-Size Effects in Productive Efficiency: A Second Test of The Passive Learning Model

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Abstract: Several studies in developed economies have reported that the rate of growth of small firms decreases with firm age as well as size. The result is consistent with Jovanovic's (1982) version of the passive learning model of competitive selection and is confirmed by data on a random sample of manufacturing firms in Ethiopia. This paper uses the Ethiopian data to test for three other implications of the Jovanovic model. These link age-size effects in firm growth to an underlying distribution of firms by technical efficiency, but have not been investigated empirically before. We find that firstly, the age-size effects detected in the growth of firms in our sample are matched by time-invariant inter-firm differences in technical efficiency. Secondly, there are also age-size effects in efficiency whereby bigger firms are more efficient given age, and older firms are more efficient given size. Thirdly, firm age and firm size mainly proxy for owner human capital and location variables in as far as they explain efficiency scores. In other words, it is not the case that some firms are more efficient than others because they are bigger or older but the other way round some firms are bigger or longer lived than others because they have proved to be more efficient. Advantageous location is a major source of technical efficiency but is not as important as greater entrepreneurial human capital. Among the human capital variables considered, the level of formal education completed has by far the strongest influence on efficiency scores. The owner's access to business networks and his or her ethnicity also have significant effects. On the other hand, there is no evidence that efficiency depends on any one of pre-ownership employment experience, occupational following of parents or prior vocational training.

1. Introduction

Data on a random sample of manufacturing firms in Ethiopia confirm findings of earlier studies in developed economies that the rate of growth of small firms decreases with initial firm size and age. The result is consistent with Jovanovic's (1982) version of the passive learning model of firm dynamics, which has often been interpreted as evidence in its favour against alternative models of selection and growth.[1] However, the possibility remains that the same age-size effects signal forces other than those portrayed by the passive learning model as driving the process of selection.[2] If age-size effects detected in the growth of groups of firms are indeed outcomes of passive learning in exit or expansion decisions, then the underlying production data must exhibit permanent and systematic inter-firm differences in technical efficiency: the current efficiency of a firm must be predicted by efficiency in the past while increasing with the current size and age of the firm. Moreover, we should be able to trace age-size effects in efficiency to the latter's dependence on entrepreneurial human capital (Lucas, 1978)[3] or locational advantage (Jovanovic, 1982) as arguably the most enduring of a firm' s characteristics.

This paper reports results of a further analysis of the Ethiopian data in what, I believe, is the first attempt to test for these further implications of the passive learning model. It deals with three questions. First, are there time-invariant inter-firm efficiency differences in the sample to match the observed age-size effect in growth? Second, is there a matching age-size effect in firm level technical efficiency? Third, do human capital and location variables sufficiently explain age-size effects in efficiency? The case for the passive learning model as an account of the mechanics of enterprise development is stronger if each of these questions is answered in the affirmative.

The seminal contribution of Farrel (1957) has led to a well developed methodological and empirical literature on the measurement of efficiency.[4] However, no previous study has examined the relationship between measured efficiency differences and growth performance in the sample of firms investigated.[5] On the other hand, none of the studies that have reported age-size effects in

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[1]The result with respect to the Ethiopian data is reported in full in a separate paper (Mengistae, 1995). Earlier reports of the same result for firm growth in developed countries include: Evans (1987); Dunne, Roberts and Samuelson (1989); Variam and Kraybill (1992); and Dunne and Hughes (1994).

[2]Other formulations of the passive learning model are Lucas (1978) and Lippman and Rumelt (1982), the relation of which to the Jovanovic model and other models of competitive selection is discussed in Mengistae (1995).

[3]The idea that entrepreneurial human capital or `management ability' is a major determinant of inter-firm differences in technical efficiency is, of course, a very old one (e.g. Marschak and Andrews, 1944) and was the theme of contributions of Mundlak (1961) and Hoch (1962) to the problem of estimation of industry level production functions. The passive learning model brings out the dynamic implication of the same differences to firm growth and longevity, thereby providing what is probably the strongest theoretical justification yet for the measurement of efficiency at the firm level.

[4]Major contributions since Farrel are: Aigner and Chu (1968); Aigner, Lovell and Schmidt (1977); Meeusen and van den Broeck (1977); Pitt and Lee (1981); and Battese and Coeli (1988). Bauer (1990) and Green (1993) provides the latest review of the literature on the subject. See also Forsund *et al.* (1980) and Schmidt (1986) for earlier reviews.

[5]Liu (1993) is the first empirical study so far (that I know of) to have analysed inter-firm differences in efficiency in the context of models of selection. The main finding of the study is that the time path of the mean level of technical efficiency is higher for incumbents than for fresh entrants which, in turn, is greater than the average efficiency of failing firms. This result is consistent with passive learning models. However, it fails to discriminate between alternative mechanisms of selection since the same outcome is also predicted by models of active learning. Neither does the study

firm growth while testing selection models has attempted to link the effects to the underlying distribution of efficiency levels, although the essence of every selection model is a distinctive hypothesis regarding such a link. Finally, it is a feature of the existing literature on firm level efficiency that variables are often chosen on an *ad hoc* basis as possible determinants of efficiency scores. We believe that existing models of selection provide a theoretical perspective that helps to bound or order the list of potential sources of efficiency among a firm's characteristics.[6] As we hope to demonstrate in this paper, the passive learning model in particular can be used to harness the econometrics of efficiency analysis for testing some of the implications of human capital and endogenous growth theory to the problem of enterprise development.

The rest of the paper is organised as follows. Section 2 sets out the econometric framework by recasting the relevant propositions of the Jovanovic model in terms of variance component formulations of the firm level production function. Section 3 gives an overview of the theoretical and empirical literature on the determinants of inter-firm differences in technical efficiency. The data are described in Section 4. Section 5 reports the results, a summary of which concludes the paper in Section 6.

2. Measuring Inter-Firm Differences in Technical Efficiency

In Jovanovic's formulation of the passive learning model, age-size effects in firm growth and survival arise from permanent but competitive inter-firm cost differences. Each incumbent and potential entrant, *i*, of an industry faces a cost function that is identical to the industry average, or frontier, up to multiplication by a strictly positive transformation $\xi(.)$ of a random error composed of two additive components, θ_i and ω_{it}. The second error component, ω_{it}, registers a purely temporary firm specific cost shock and is assumed to be distributed i.i.d. normal with mean zero and variance σ_ω^2. The component θ_i is a fixed measure of the cost advantage of the firm, such that the larger is its value the higher is the cost of production of a given output relative to the cost that is average, or minimal, to the industry. However, its true value is unknown to the firm, which only knows that θ_i is a random draw from the distribution $N(\mu_\theta,\sigma_\theta^2)$ common to all potential entrants. Draws from the distribution are independent across firms and each firm knows μ_θ, σ_θ and the exact form of $\xi(.)$. Because θ_i is unknown, production decisions are based on what the firm estimates it to be, given past realisations of $\xi(\theta_i + \omega_{it})$. Under certain regularity conditions, the precision of this estimate increases with the duration of the firm's stay in the current industry. Production thus coincides with a learning process through which the firm gradually discovers the extent of its competitive advantage. Firms for which the true value of θ_i is too high experience a series of bad cost shocks, $\xi(\theta_i + \omega_{it})$, and are eventually forced to exit. Firms for which θ_i is relatively low experience a better series of shocks, stay put and grow. For firms that do survive the selection process, the rate of growth decreases in firm size and firm age.

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directly examine the link between efficiency and growth performance among surviving firms, which is the focus of this study.

[6] An example of this function of models of selection is the hierarchy established by passive learning models between firm size and firm age on the one hand, and entrepreneurial human capital and location on the other, in the determination of firm level efficiency scores. To the extent that age-size effects in efficiency signal passive learning, they merely proxy for human capital and location variables.

Let C_{it} be the total cost of production of output Q by firm i during period t. Let $C(.)$ be a cost function with the usual properties that is average or frontier to the industry. The firm level cost function assumed in the Jovanovic model is:

(1) $$C_{it} = C(Q)\xi(\Theta_i + \varpi_{it}) \quad .$$

By the principle of duality, θ_i is a monotonic and strictly decreasing transformation of a firm specific productivity parameter u_i, while ω_{it} is a similar transformation of a purely temporary and firm specific random productivity shock ν_{it}. We will assume that the production function underlying equation (1) can be written as:

(2) $$Q_{it} = h(z,\beta)\exp(u_i + \upsilon_{it}) \quad ,$$

where Q_{it} is the output of firm i during period t for a given vector of inputs z, β is a vector of parameters and

(3) $$\xi(\theta_i + \omega_{it}) = \delta\,[\exp\,(u_i + \upsilon_{it})] \;\; , \;\; \delta' < 0 \quad .$$

For comparability of results to those of previous empirical work, we will further assume that the production function is Cobb-Douglas and estimate

(4) $$y_{it} = \beta_o + \Sigma_j \beta_j x_{jit} + \upsilon_{it} + u_i \quad ,$$

where m is the number of factor inputs, y_{it} is the log of Q_{it} and x_{jit} is the log of z_{jit}.

Because θ_i is assumed to be a random draw from a known common distribution so is u_i.We will denote the variance of u_i by σ_u^2. We will also assume that ν_{it} is distributed i.i.d. normal with mean zero and constant variance σ_υ^2. In the absence of any restriction on the value of u_i, the expectation of the sum of the first three terms on the right hand side of equation (4) defines the average production function of the industry from which the deviation of the production technique of firm i, given output, is measured by u_i.

A key prediction of the passive learning model is that u_i is correlated with firm size and, therefore, with input levels x. We will refer to equation (4), together with the assumption that there is indeed such correlation as the fixed effects average production model of inter-firm efficiency differences.[7] This follows Hsiao's (1986) distinction between the fixed-effects and random-effects specifications of variance component models on the basis whether or not individual effects are correlated with regressors. The covariance estimator of this model is BLUE, while the corresponding GLS estimator is biased and inconsistent (Mundlak, 1978). On the other hand, the GLS estimator is consistent and attains the Cramer-Rao lower bounds under the alternative random effects average production function model. Since the covariance estimator is also consistent in the case of the latter model, Hausman's (1978) test of the fixed effects average production function model is a way of testing whether efficiency depends on firm size. One way of testing for the permanence of inter-

[7]This is the formulation used in early work on the modelling of inter-firm efficiency difference, namely, Mundlak (1961), Hoch (1962) and Timmer (1971).

firm efficiency difference is to conduct the Breuch-Pagan Lagrange Multiplier test of the OLS formulation of equation (4), against the random effects average production function model. Alternatively, we may carry out a likelihood ratio test of the OLS model against the fixed effects model. This follows from the fact that estimators of the parameters of equation (4) are BLUE only if the restriction of no firm effects is valid in both the fixed effects and random effects formulations of the average production function.The restriction amounts to that $u_i = 0$ in the fixed effects model and to that $\sigma_u^2 = 0$ in the random effects model. In both cases it means $E(\varepsilon_{it},\varepsilon_{is}) = 0$ for all $t \neq s$, where $\varepsilon_{it} = u_i + \nu_{it}$.This in turn implies that $E(\varepsilon_{it}^2)=\sigma_\upsilon^2$.

Together with the assumption that u_i is uncorrelated with input levels, the restriction $u_i \leq 0$ makes equation (5) a random-effects production frontier model. In this case the sum of the first three terms of the right hand side of the equation becomes the stochastic frontier introduced into the literature by Aigner *et al.* (1977) and Meeusen and van den Broeck (1977). With additional distributional assumptions about u_i, the random-effects production frontier can be estimated by maximum likelihood, which is more efficient than Feasible GLS, since the latter cannot use the restriction that u_i is non-positive.[8] The assumption most commonly used is one of: u_i is half-normal; u_i is truncated normal; or u_i is negative exponential. For computational convenience, we will assume in the rest of the paper that u_i is exponential with parameter λ.

Given the random effects frontier model, the technical inefficiency of firm *i* is measured by exp. u_i. Battese and Coeli (1988) have proposed an unbiased and consistent predictor of $|u_i|$, which is given for the unbalanced panel case by:

$$\tilde{u}_i = \bar{E}(u_i / \varepsilon_{i1},\ldots,\varepsilon_{iTi}) = \hat{E}_i + \psi_i[\phi(\hat{E}_i / \psi_i) / \Phi(\hat{E}_i / \psi_i)] \quad , \tag{5}$$

where $\phi(.)$ is the standard normal pdf; $\Phi(.)$ is the standard normal cdf; e_{it} is the residual corresponding to the observation on firm *i* at time *t*; T_i is the number of observations on firm *i*; and the hat symbol over λ, σ_u, σ_ν and σ_ε indicates the maximum likelihood estimate of the corresponding parameter.

$$\hat{E}_i = \hat{\Gamma}_i\hat{\lambda} + (1-\hat{\Gamma}_i)\bar{e}_i \quad ; \quad \hat{\Gamma}_i = 1 + (\hat{\sigma}_u / \hat{\sigma}_\upsilon)\, T_i \quad ; \quad \bar{e}_i = T_i^{-1}\sum_{t=1}^{T_i} e_{it} \quad ; \quad \psi_i = \hat{\sigma}_\varepsilon^2\sqrt{\hat{\Gamma}_i} \quad ;$$

The measure of inefficiency in the fixed effects average production function model is:

$$\hat{\alpha} = \max(\hat{u}_i) - \hat{u}_i \tag{6}$$

where $\hat{u}_i$ are estimated firm fixed effects.

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[8]This amounts to saying that GLS cannot discriminate between the average production function and production-frontier formulations of inter-firm efficiency differences.

The likelihood ratio test of the random effects frontier model against the alternative that $\varepsilon_{it} = \nu_{it} + u_i$ is distributed i.i.d. normal with mean zero and variance σ_υ^2 is a test for the existence of permanent inter-firm differences in technical efficiency. The LM test of the random effects average production function model against the OLS alternative performs the same function. The likelihood ratio test of the random effects frontier model against the fixed effects model tests the assumptions of the former regarding the distribution of u_i. More significantly from our point of view, it also tests the null that u_i is independent of firm size.

In the remaining sections of the paper we will refer to equation (4) under the Gauss-Markov assumptions as `Model I'; to the random-effects frontier production model as `Model IIA'; to the random-effects average production function model as `Model IIB'; and to the fixed effects model as `Model III'. We will estimate Model I by ordinary least squares on pooled cross-section and time series data for each of seven industries. The data are an unbalanced panel of annual observations over a three-year period which we describe in detail in Section 4. Models IIA and IIB will be estimated by maximum likelihood and Feasible GLS respectively for each industry.[9]

3. Identifying Firm-Specific Sources of Technical Efficiency

There are three alternative approaches to the analysis of inter-firm efficiency differences. The oldest of these was first used by Timmer (1971), who regressed estimated Farrel measures of technical efficiency on firm characteristics of interest by ordinary least squares. As pointed out by Kumbhakar *et. al* (1991), this may not be appropriate since the dependent variable is bounded between zero and one. A better method is to apply limited dependent variable techniques of estimation as is done, for example, in Martin and Page (1983), Kalirajan (1990) and Reifschneider and Stevenson (1991). Alternatively, we can replace the Farell measure as the dependent variable by a score of efficiency that is a positive, monotonic transformation of the former but is unrestricted in domain (Lovell, 1993). The problem with this approach is that, if input levels are correlated with technical efficiency contrary to what Model IIA assumes, they will also be correlated with the very firm characteristics that are supposed to explain the variation in efficiency. Parameter estimators of the production frontier will therefore be biased. Since the bias might carry over to predictions of efficiency, the technique should be used only if the Hausman test decisively rejects the fixed effects model.

The second approach to the analysis of technical efficiency was first used in Pitt and Lee (1981). It avoided the bias inherent in the first approach by including firm characteristics among the regressors in the estimation of the production frontier. The appropriate specification of the frontier of Model IIA is in this case:

$$(7) \qquad y_{it} = H(x, c{:}\beta, a) + \upsilon_{it} + u_i \quad ,$$

where c is a vector of firm characteristics and a is the vector of the corresponding coefficients. The role of individual characteristics in explaining efficiency is then assessed by means of the usual

[9]The extension of balanced panel techniques of estimation of the random effects model to the case of unbalanced panels is discussed in Hsiao (1986) and Baltagi (1995). Pitt and Lee (1981) derive the likelihood function of Model IIA for the balanced panel case with normal-half-normal error terms. See Green (1991 pp 667-773) for the log-likelihood function of the normal-exponential model estimated here.

specification tests and by looking at what happens to the estimate of σ_u^2 as we include the characteristic in the specification of the frontier. Unfortunately, the approach is likely to lead to a problem of multicollinearity. The rationale for its use is, after all, that input levels are sufficiently correlated with the firm characteristics now added to the specification of the production function.

The third approach consists of the ordinary least squares regression of estimates of firm fixed effects of Model III on firm characteristics. It was again first used by Pitt and Lee (1981). The method is not subject to the omitted variable problem of the first approach or the multicollinearity problem of the second. It is therefore the best available method when the random-effects formulation is comfortably rejected in favour of fixed effects. Its advantage disappears, though, when input levels are uncorrelated with individual firm effects. In this case, predictions of firm level efficiency based on the approach may be less efficient than their random-effects alternatives.

Only results of the first and the third approach will be reported later in this paper. As expected, the inclusion of firm characteristics in the specification of the frontier under Model IIA led to a serious multicollinearity problem. On the other hand, a choice could not be made between the first and third approaches. This was because scores of efficiency had to be regressed on firm characteristics over the full sample of firms, while production functions were estimated for sub-samples of individual industries. As will be reported later in detail, the random-effects model was rejected in favour of the fixed effects model for some industries but not for others. The use of only one of the two in the regression of efficiency scores pooled across industries could not, therefore, have been justified.

The score of relative technical efficiency used in applying the first approach is denoted by DPANU and is defined as the deviation of the Battese-Coeli predictor, $\tilde{u}_i$ from the industry sample mean. The transformation is strictly increasing in the Battese-Coeli predictor but is unbounded in domain. It also has the added role of filtering out the bias possibly arising from inter-industry differences in sampling error.[10] Since the bias is also potentially present in the use of the third approach, a similar transformation of estimated firm fixed effects, denoted by SCOREF, is used as a dependent variable instead of individual firm effects. The variable SCOREF is defined as the deviation of firm fixed effects from the industry sample mean of the effects expressed in units of the industry standard deviation. The Battese-Coeli predictor, $\tilde{u}_{i\cdot}$, will be denoted by PANU as a dependent variable. Firm-fixed effects will be denoted by FIXED.

Our choice of regressors is based on two of the implications of the passive learning model. The first of these is that there are age-size effects in efficiency. The second is that firm age and firm size proxy for entrepreneurial human capital and locational advantage in as far as they explain efficiency scores. Greater efficiency leads to higher firm size or longevity and not the other way round. If the first proposition is correct, then owner human capital and location variables should entirely explain observed inter-firm efficiency differences with due allowance for sampling error. If the second proposition is correct, the regression of efficiency scores on firm age and firm size only should have at least as much explanatory power as the alternative regression of the same scores on human capital and location variables. In other words, coefficients of age-size variables would not be significant in an equation in which owner human capital and advantageous location are fully controlled for, or vice versa. A result to the contrary should then be interpreted to mean that not all the observed age or size effects in efficiency can be attributed to passive learning. In particular,

[10] The addition of industry dummies in the efficiency score regressions no doubt helps to minimise the bias. However, there is no guarantee that it will eliminate it entirely.

a size effect that survives the inclusion of human capital and location variables should have additional or alternative sources such as economies of scale and competitive diffusion.[11] Likewise, age effects that would fail to disappear when we add the same variables signal other sources such as the influence of firm age on replacement costs of capital and, hence, on effective choice of technique.[12]

Inter-firm efficiency differences are entirely competitive in the passive learning model. However, this is an assumption that is unlikely to hold in our data. Firms in the sample are distributed across industries that may differ significantly in terms of the `competitive pressure' faced by the individual firm. That the mean firm level of efficiency of an industry depends on this particular factor is, indeed, the theme of much of the empirical literature on efficiency analysis that seeks to assess the impact of trade or regulatory policy on the performance of particular industries. We therefore include industry dummies as the third set of regressors in the efficiency score equations. As already pointed out the coefficients of this set of variables may well be biased due to systematic inter-industry differences in sampling error if the dependent variable is either FIXED or PANU. However, the bias should not be present when the dependent variables are replaced by SCOREF or DPANU.

We have grouped measures of owner human capital into three sets of variables: namely, measures of schooling, indicators of informally acquired skills and indicators of access to business networks. The variables in the first set have been used in at least one previous study of the determinants of firm level technical efficiency (Kalirajan, 1990) which found that years of formal schooling was a significantly positive influence on efficiency among commercial rice farms in the Philippines. If the implication of passive learning to the relationship between efficiency and firm longevity holds, this result is also confirmed by Bates (1990), who found the probability of survival to increase in years of owner schooling for a sample of U.S small businesses. To my knowledge, the prior employment experience of the firm owner in the current industry is the only variable in the second set to have been used in a previous study of efficiency.[13] However, Bates (1990), Lentz and Laband (1990) and Holtz-Eakin *et al.* (1994) examined the role of some of the other variables in the determination of size or longevity among small businesses in the US. In the Letnz and Laband study, family background (measured as whether the owner was a `second generation' business owner in his or her family tree) was found to be more important than formal schooling as a determinant of business success (as measured by firm size). On average, second generation business owners ran bigger firms than first generation owners, when years of schooling; business assets at start up; and the length of pre-ownership experience in the current industry were all controlled for. In contrast, the influence of years of schooling was not statistically significant, which the authors interpreted to imply that the skills that second generation owners acquired by virtue of being brought up in the

[11]The distinction between passive learning, competitive diffusion and scale economies as sources of size effects in firm growth and efficiency is discussed in Mengistae (1995).

[12]Pitt and Lee (1981) advance this factor as a possible explanation to their finding that younger firms were more efficient in the sample of Indonesian weaving firms they studied. Their argument is broadly consistent with Lambson's (1991) thesis that age effects in firm level efficiency and growth performance can arise under competitive conditions, even in the absence of passive or active learning, if firms differ in sunk costs and have to make production and exit-entry decisions under market uncertainty.

[13]The age of the owner and the number of years of the owner's prior experience in the industry of the current business are two of the variables that Martin and Page (1983) used in explaining technical efficiency in two Ghanian industries.

environment of a family business was a better asset to a business career than formal education.[14] This finding contradicts that of Bates, who found family-background variables to have had little or no influence on firm size. Holtz-Eakin et al. report that the same variables also failed to explain variation in the probability of business survival.[15]

There are three variables in the third set: one of which is the ethnicity of the owner; the others indicate his or her access to business networks as sources of information or other forms of business support. To my knowledge, none of these variables has been used in a previous study of firm level efficiency. However, Fairlie and Meyer (1994) found that owner ethnicity was a significant determinant of the size of immigrant owned firms in the U.S, when owner age, years of education and years of immigration were controlled for. Their interpretation of the result is that it may suggest that business information and mutual support networks tend to form along ethnic lines and that some ethnic groups are better than others in terms of `ability to transfer information to and from co-ethnics'.[16] Alternatively, the result may signal ethnic externality in the formation of business skills (Borjas, 1992). This is in the sense that the skill of a family generation may depend not only on parental investment in the formal or informal training of children, but also on `the average quality of the ethnic environment' in which the same investment is made, i.e. on what Borjas calls `ethnic capital'. If there is indeed such an externality, then the same amount of investment in the `education' of children results in different levels of skill formation across ethnic groups. Moreover, if the externality is strong enough, ethnic differences in skills and patterns of comparative advantages in trades or occupations will persist across generations.[17]

4. Data

4.1. Source

Our data are drawn from the results of the 1993 wave of the Addis Ababa Industrial Enterprises Survey for the design and implementation of which the author was responsible.[18] The survey covered a random selection of 220 firms in several manufacturing industries in the Addis Ababa region of Ethiopia. The sample consisted of 190 private firms and 30 public enterprises. The survey instrument was a questionnaire in 10 modules, of which 9 were administered to firm owners or general managers in a face-to-face interview by a member of the research team. The data used in this particular study were generated by questions selected from four of the nine modules, namely, those dealing with: (a) production, cost and employment figures; (b) current capital stock and recent

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[14]See also Laband and Lentz (1983) for details of the underlying argument.

[15]Holz-Eakin *et al.* found the age of the owner to be a significant determinant of firm survival.

[16]Their interpretation draws on some of the sociology literature on the determinants of entrepreneurial success such as Light (1984), Zimmer and Aldrich (1987) and Aldrich and Waldinger (1990).

[17]Borjas' argument is based on a narrowed down version of Coleman's (1988) concept of `social capital' and is very much in the spirit of the endogenous-growth literature (e.g. Romer, 1986; and Lucas, 1988).

[18]The round is the first in a survey series designed to generate panel data sets on various aspects of enterprise development in manufacturing industries in Ethiopia, and is a joint project of the Department of Economics of the Addis Ababa University, the Centre for the Study of African Economies of the University of Oxford and the Free University of Amsterdam.

fixed investment; (c) history of establishment of the firm and the employment history and family background of the owner; and (d) owner participation in business networks and social organisations.

Data used in the estimation of industry level average or frontier production functions were generated by questions in the first two of the four modules. Data on owner human capital and location variables used in efficiency score regressions were generated by the last two modules. The latter include the age of the firm, indicators of the location of the firm relative to suppliers, clients and competitors; the age, sex, marital status, household size and ethnicity of the owner; personal wealth of the owner's family; the highest level of formal education attained by the owner; the major occupation of the parents of the owner; the pre-ownership employment status of the owner; the length of pre-ownership experience of the owner in the current industry of the firm; the owner's participation in apprenticeship and formal vocational training programmes prior to the establishment of the firm; the owner's participation in informal credit or social organisations; and the owner's rating of relatives, friends, and other business people as alternative sources of business information.

4.2. Age-Size Effects in Firm Growth

An earlier analysis (Mengistae, 1995) shows that the rate of firm growth in our sample decreases with initial firm age and size. A summary of this result is presented in Table 1 for the full sample of firms over the period 1989-93, which is also the period of the production data analysed in this paper. In each row of the table is our estimate of Gibrat's equation of firm size for the indicated time interval. In each case the dependent variable is the log of end-of-period employment size of the firm, CSIZE. The regressors are: the log of beginning-of-period employment size, SIZE; the log of beginning-of-period age of the firm, AGE; and an ownership dummy variable, PUBLIC, which assumes a value of unity for public enterprises. A coefficient of less than one for SIZE implies that the rate of firm growth decreases in size. An inverse relationship between growth and age is indicated by a negative coefficient for AGE. Public enterprises are included in the estimation of the growth equations as well as the estimation of the average or frontier production functions reported below. However, the efficiency score regressions to be reported later refer only to privately owned firms.

4.3 Production Variables

The estimated production functions reported in the following section are based on a panel of annual data on the volume of production, number of employees and capital stock for the years 1989, 1991 and 1993. Output is defined as annual value added, expressed at 1993 prices based on the Addis Ababa retail price index. Value added in turn is defined as annual production less the cost of raw materials and utilities. Actual figures on the latter are available only for 1993. Value added figures for the years 1989 and 1991 are therefore computed from production figures on the assumption that the ratio of value added to gross output observed in 1993 also applied for the other two years. Labour services are measured by annual man-hours. Capital services are measured by annual energy consumption at 1993 prices. Both input variables are the same as those used in Pitt and Lee (1981), whose findings we will be comparing with ours in some of the discussion in Section 5. An alternative measurement for capital services, first proposed by Hoch (1962), is depreciation plus annual interest charges on capital stock at the going bank long term lending rate, which we also tried to use. However, the coefficient of capital generally turned out to be negative.[19]

Each of the production functions specified in Section 2 is estimated separately for six four- digit industries and a seventh category of firms in a miscellany of industries, of which the most important are the weaving, chemical, rubber and paper industries. The six four-digit industries are: bakery products (SIC 1541); furniture making (SIC 3610); garments (SIC 1810), knitting (SIC 1730); leather footwear (SIC 1920); and structural metal products (SIC 2811). Not all firms in the sample were in operation in 1989, approximately a fifth of them having been set up in 1990 or later. This, and the omission of firms with missing values for one of the three variables of the production function, resulted in 515 observations on 198 firms out of what could have been a total of 660 observations. Table 2 provides descriptive statistics of the production variables used by industry. The variables are: LABOUR, defined as the log of total annual man-hours; CAPITAL, defined as the log of annual consumption of energy at 1993 prices; and OUTPUT, defined as the log of annual value added at 1993 prices.

4.4 Data on Firm Characteristics

Descriptive statistics of regressors of the efficiency score equations are given in Table 3. The variable LNSIZE represents firm size and is defined as the log of the average employment size of the firm in 1989, 1991 and 1993. LNAGE is the log of the age of the firm in 1993. AGESQ is the square of LNAGE. The location variables in the table are: SURROUND, which is a dummy variable equal to 1 if the main business premise of the firm is in the middle of those of the firm's competitors; OWPREM, which is a dummy variable equal to 1 if the firm owns its business premises; and GOVRENT, which is a dummy variable equal to 1 if the firm's premises are rented from the central government. Non-residential urban land and property in Ethiopia is mostly government owned following the nationalisation law of 1975. 51% of private firms in the sample own their business premises. Some of these are firms which operated on own property prior to the nationalisation and were allowed to keep ownership of the premises by the new law. Others are establishments set up after the nationalisation on converted residential property, usually having failed to secure sites in the now government owned industrial areas. There are two forms of access to such areas at the moment. One is renting buildings owned by the central government. The second is tenancy to local or municipal authorities. The first is the case with 25% of firms in the sample. Another 24% operate on premises rented from the local authority. Buildings rented from the central government are larger, better designed, better provided for in infrastructure, and of closer proximity to business centres compared to those under municipality ownership, which in turn are better suited for business than privately owned premises. The allocation of tenure to government or municipal property is purely one of administrative rationing at rents that are generally believed to be far below current opportunity cost. Our hypothesis is therefore that tenants of the central government (GOVRENT) generally have an advantage in location over those operating on own property (OWPREM) or on municipal property. If it indeed exists, such an advantage should be revealed through higher technical efficiency. The variable SURROUND is an alternative measure of locational advantage. Its use is justified by the fact that business premises in Addis Ababa are heavily concentrated in particular parts of the region, each of which has come to be regarded as the `home' of a particular industry and is presumably the preferred location of

[19]It is interesting that the same outcome was reported by Hoch.

potential entrants to the industry. Proximity to a larger number of competitors is one possible indicator of access to such established sites.

4.5 Owner Human Capital Variables

The definition of the human capital variables included is as follows:

LNEXPER	=	log of the number of years of experience the owner had in the present industry prior to setting up or acquiring the firm;
APPRENT	=	a dummy variable equal to 1 if the owner had ever been an apprentice;
PRIMARY	=	a dummy variable equal to 1 if the owner had completed primary school as his or her highest level of formal education;
SECOND	=	a dummy variable equal to 1 if the owner had completed secondary school as his or her highest level formal education;
COLLEGE	=	a dummy variable equal to 1 if the owner had completed a regular course in an institution of higher education;
VOCATION	=	a dummy variable equal to 1 if the owner had completed a regular vocational course in an institution of formal education;
OWNBUS	=	a dummy variable equal to 1 if the career of at least one of the parents of the owner was running a non-farm business;
PUBEMP	=	a dummy variable equal to 1 if the career of at least one of the parents of the owner was as a public sector employee;
PRIEMP	=	a dummy variable equal to 1 if the career of at least one of the parents of the owner was as an employee of ap private non-farm firm;

The variables PRIMARY, SECOND, COLLEGE and VOCATION are expected to capture the influence of formal education of the owner on efficiency scores. The Ethiopian education system consists of six years of primary school followed by six years of secondary school, at the end of which successful candidates may proceed to programmes of tertiary education lasting 2 years or more in universities, polytechnics or junior colleges. Formal vocational training programmes last between two and four years and are offered by comprehensive high schools or specialised technical colleges. 12% of owners of firms in the sample had not completed primary school when they started their businesses; 27% had completed primary school but had not proceeded to secondary classes or had dropped out before sitting for the school leaving certificate examination; 45% had completed secondary school; and 16% had completed a course of tertiary education. Just over 20% had full-time vocational training.

More than 50% of owners in the sample started their career as young apprentices, mostly in the field of the present firm. The variable APPRENT should capture the influence of business skills that they might have picked up in the course of this experience. The variable LNEXPER is intended to represent skills that may have been acquired in the entire pre-ownership employment experience of the owner in the present industry as an employee, a self-employee, an apprentice or as an occasional helping hand in a family enterprise. Approximately 70% of owners in the sample had some kind of experience in the industry prior to starting or acquiring the current firm, the most important form of experience being wage-employment in another firm (34%); followed by self-employment (21%); and `working and learning the trade at home' (19%).

In one sense, the variables OWNBUS, PUBEMP and PRIEMP also belong to the category of experience variables. However, unlike LNEXPER or APPRENT they are not limited to experience in the field of the current firm and should pick up the impact of parental occupation on the formation of business related skills. Only about 5% of owners of firms in the sample had a parent who owned a manufacturing establishment. However, 35% of them had a parent who ran a trade or service business. The parents of another 39% were traditional small farmers. About one fifth of owners had a parent who worked as an employee of a private firm or in the public sector.

The regressors relating to the ethnicity of owner and his or her access to business or social networks are the following:

FELLOW	=	a dummy variable equal to 1 if the owner of the firm ranked relatives or friends as the most important sources of information to his or her business;
LNWEALTH	=	log of the personal wealth of the owner and members of his or her family excluding business assets;
OTHERBUS	=	a dummy variable equal to 1 if the owner of the firm or members of his or her family own another business;
AMHARIC	=	a dummy variable equal to 1 if the owner of the firm belongs to the Amharic ethnic group;
GURAGE	=	a dummy variable equal to 1 if the owner of the firm belongs to the Gurage ethnic group;

In order to assess the access of firms to business networks, firm owners were asked in the survey to identify what they regarded as the most important source of information to their business from a list of possibilities that we have grouped into the variable FELLOW, and `other business'. The latter groups the responses `other business men as clients',`other businessmen as suppliers', and `other business men in the same industry', which together account for 56% of the responses against 26% responses under FELLOW. Our hypothesis is that those who use relatives or friends as their most important source of business information have no (or restricted) access to business networks and are, therefore, at a disadvantage, which should translate to lower scores of efficiency of their firms than those whose most important sources of information are `other business men'. The variables LNWEALTH and OTHERBUS are included to take into account the possibility that an owner's access to business networks depends on his or her `social standing' within an ethnic or a professional community which, in turn, might depend on the wealth of the owner as indicated by LNWEALTH or the number of businesses owned. Thirty two of firm owners in the sample own at least one other firm.

In the light of the discussion in Section 3, the two ethnicity variables, AMHARIC and GURAGE, may perform one or both of two functions. On the one hand, they can indicate externality in the formation of entrepreneurial skills of firm owners in the sense of Borjas (1992). On the other, they may be measuring the owners' access to business networks in as far as these are formed along ethnic lines. Either way, the hypothesis is that the ethnicity of the owner is a significant influence on the efficiency score of the firm. 40% of firm owners in the sample belong to the Amharic ethnic group, against 32.6% who belong to the Gurage ethnic group. The popular wisdom in Ethiopia at present is that the Gurage have exceptional business acumen and a greater tendency to form mutual business support schemes along kinship lines. A Gurage is therefore generally perceived to have a greater chance of succeeding in a business venture than a member of any other ethnic group in Ethiopia. If this is indeed the case, the efficiency scores of firms under Gurage ownership should be higher, other things being equal.

The last set of regressors in the efficiency score regressions consists of industry dummies which we define as follows:

BAKERY	=	a dummy variable equal to 1 for firms producing bakery products (i.e.,SIC 1541);
FURNITUR	=	a dummy variable equal to 1 for firms producing furniture (i.e.SIC 3610);
GARMENT	=	a dummy variable equal to 1 for firms producing wearing apparel excluding knitwear (SIC 1810);
KNITTING	=	a dummy variable equal to 1 for firms producing knitwear (SIC1730);
LEATHEREF	=	a dummy variable equal to 1 for firms producing leather products (SIC 1920);
METALWOR	=	a dummy variable equal to 1 for firms producing structural metal products (SIC 2811).

5. Results

5.1 Testing for Inter-Firm Differences in Technical Efficiency

The pooled-data least squares estimation results of Model I are reported by industry in Table 4. They are the basis for testing the hypothesis that there are time invariants in inter-firm differences in technical efficiency to match the age-size effects in growth detected in the data. The goodness of fit of the model is comparable in every case to those reported in many other least square estimates of the Cobb-Douglas function on manufacturing micro data of developing countries, including those of Haddad (1993); Liu (1993); Page(1980); Pitt and Lee (1981); and Tybout and Corbo (1991). A common result of these studies is that the elasticity of output with respect to labour input is several times larger than output elasticity with respect to capital, which is also the case reported here. Note also that the assumption of constant returns to scale cannot be rejected for any of the industries. This applies to estimates based on fixed as well as random effects (Tables 5-7) and is of interest in the interpretation size effects in firm level efficiency.

Table 5 reports results of the ML estimation of Model IIA. Results of the Feasible GLS estimation of Model IIB are reported in Table 6. Estimation results of Model II are given in Table 7. The null that there are no inherent inter-firm differences in technical efficiency is rejected in favour of each of the three models. Beginning with tests based on Model IIA, the likelihood ratio test rejects Model I, or the restriction that $\sigma_u^2 = 0$, at the 5% level for all industries except one. Indeed, the estimate of σ_u^2 exceeds that of σ_υ^2 in two of the industries and is only the slightly smaller variance component of the rest. The same restriction is rejected even more decisively in relation to Model IIB by the Breuch-Pagan LM test for which the test statistic is significant at almost any level in all the industries. The estimate of σ_u^2 is also greater than that of σ_υ^2 in five of the industries and is far from being `swamped' by the purely temporary component in the other two. A similar result is obtained with respect to Model III, where the null of no firm fixed effects is rejected by the likelihood ratio test at the 1% level or less for every industry.

5.2 Age-Size Effects In Firm Level Efficiency

As already pointed out, the Hauseman test of Model IIB against Model III in effect tests for a size effect in technical efficiency when size is measured by the scale of input usage. The test rejects the random effects formulation only for three of the seven industries. This somewhat contrasts with the results reported in Table 8, where age-size effects in efficiency are evident regardless of whether the efficiency scores are based on the fixed effects model or on the random effects formulation. The scores of efficiency used in the regressions of the first two columns of Table 8 are based on estimates of Model III. Those used in the regressions reported in the last two columns of the same table are based on estimates of Model IIA. In all columns of the table firm efficiency increases in size. Older firms are also more efficient until some age threshold is reached beyond which efficiency seems to decrease with age. Both outcomes are consistent with the predictions of the passive learning model. The result that bigger firms are more efficient is also consistent with the findings of Pitt and Lee (1981) in their study of Indonesian weaving firms. The result that efficiency increases with firm age below some threshold age is consistent with the findings of Martin and Page (1983) for a sample of firms in the Ghanaian wood industry and with those of Haddad (1993) for a sample Manufacturing firms in Morocco. However, it contradicts the result of Pitt and Lee who detected a negative age effect in efficiency. One possible explanation of the Pitt and Lee result is that their sample is truncated in age above the threshold level detected here. It is, of course, also possible that their suggested explanation that the effect is due to sunk costs impeding choice of technique by older firms is correct — at least for their sample.

5.3 Firm Characteristics and Efficiency

That the age-size regressors in the efficiency score equations of Table 8 do indeed proxy for entrepreneurial human capital and locational advantage can be seen from Tables 9 and 10. This result comes out more forcefully in the random effects model than in the fixed effects formulation. Table 9 reports results of the regression of scores of efficiency on firm characteristics including firm age and firm size. The age-size variables are excluded from the regressions of Table 10. The F-test fails to reject the exclusion at the 5% level in all cases. Moreover, contrary to what we see in Table 8, neither age nor size is any longer significant in the regressions based on the random effects regression of Table 9. The influence of age on fixed effect efficiency scores reported in Table 8 also disappears in Table 9 as we add human capital and location variables. However, the effect of size on fixed effect efficiency scores persists between the two tables. This suggests that some of the size effect registered in the first two columns of Table 8 may be a result of sources other than differences in entrepreneurial human capital or location. Of two of such sources suggested earlier, economies of scale seems to be ruled out by the fact that we are unable to reject the null of a constant-returns-to-scale technology for any of the industries based on the estimates of Tables 4-7.

Turning to the effect of individual location variables, we see from both Tables 9 and 10 that `advantageous location' is a stronger influence on fixed effect efficiency scores than it is in the random effects model. This is particularly the case in the regressions in which the score is SCOREF. In this case all the three location variables are statistically significant, have the expected sign and are of the same order of magnitude as those of LNAGE in the corresponding regression in Table 8. Changing the dependent variable to FIXED does not alter the result much except that the standard errors of the coefficient of SURROUND become considerably larger. The regression results based on random effect efficiency scores are consistent with those of the fixed-effect model in terms of the signs of estimated coefficients (columns 3 and 4). However, only one of the location variables, namely GOVRENT, is significant in this case.

The fixed-effects and random-effects specifications are in almost full agreement when it comes to the role of owner human capital variables. Firstly, in both cases levels of formal education exert a far stronger influence on efficiency than any of location or other human capital variables. The coefficient of each of the variables, PRIMARY, SECOND and COLLEGE is positive, significant at the 1% level and greater in magnitude than that of any of the other human capital or location variables. Secondly, skills that firm owners may have acquired informally prior to setting up their businesses, as indicated by APPRENT or LNEXPER, do not seem to influence technical efficiency in either case. The same applies to technical skills acquired through formal training as indicated by VOCATION. If anything, the negative signs of the coefficients of the three variables suggest that firms whose owners have had longer pre-ownership experience and vocational training are less efficient. A possible explanation for this is that owners that have had the longest pre- ownership career in an industry as trainees or employees, tend to set up a business of their own in the same industry, or tend to stay put less because they are convinced of their competitive advantage over new comers than because their relative efficiency would be even lower elsewhere.[20] Probably for the same reason, we find that firms of `second generation' businessmen are less efficient than those of `first generation' firm owners. The coefficient of the variable OWNBUS is negative and significant in the regression of firm fixed effects, while the variable PUBEMP is positive and significant in the regressions of PANU and DPANU. The result is consistent with those of Bates (1990) and Holtz-Eakin *et al.* (1994) but contrary to what Lentz and Laband (1990) reported.

Of the variables indicating access to business networks, FELLOW and OTHERBUS are significant with the expected sign in all the equations of Tables 9 and 10.[21] The result suggests that technical efficiency is higher the greater the access of the owner to business networks extending beyond relatives or friends. We also see that the ethnicity of the owner is correlated with a firm's efficiency. As pointed out earlier, this may be due to ethnicity determining the quality or extent or scope of the business networks the owner is able to access. Alternatively, it may reflect the effect of ethnicity as a source of externality in the formation of the owner's skills. Of the two ethnicity variables considered, AMHARIC is negative and significant in all the four equations, suggesting that firms run by Amharic business men are doing generally worse than other firms. However, the other variable, GURAGE, is negative and not significant, which does not agree with the popular view of the Gurage as the most likely to `succeed in business' among all the ethnic groups in Ethiopia, at least in relation to manufacturing businesses.

We finally note that the evidence for an industry effect in firm level efficiency is rather mixed. The relevant results in this connection are those of the regression of SCOREF or DPANU on firm characteristics, since coefficients of estimates of industry dummies in the other regressions are clearly biased as estimates of industry effects by inter-industry differences in sampling error. Using

[20]We note that our result that LNEXPER is not a significant influence on technical efficiency contrasts with the findings of Martin and Page (983)for a sample of industrial firms in Ghana.

[21]The variable LNWEALTH has the expected sign but is not statistically significant in any of the equations.

the SCOREF or DPANU we see that there are significant industry effects in efficiency according to the fixed effects model, but practically none according to the random effects formulation.

6. Summary and Conclusion

Using data on a sample of manufacturing firms in Ethiopia, this paper reports further evidence in favour of Jovanovic's version of the passive learning model of competitive selection. Several studies of firm growth in developed economies have found that the probability of survival of firms increases in firm size and age, while the growth rate of a firm conditional on survival decreases in both variables. This result is consistent with the Jovanovic model and, as reported in a companion paper, is also supported by the data analysed in this paper. The main contribution of the paper is the testing of three other implications of the passive learning model for the first time. The first is that age-size effects in growth or survival imply permanent inter-firm differences in technical efficiency. The second is that there are age-size effects in firm level efficiency whereby older firms are more efficient given size, and bigger firms are more efficient given age. The third is that the direction of causation is not from firm age or size to efficiency, but the other way round. Age-size effects in firm level efficiency should therefore be traced to the influence on efficiency of more enduring firm characteristics such as entrepreneurial human capital and location.

We have argued that the passive learning model implies a fixed effects distribution of techniques relative to a frontier or an average production function.The null that there are no firm effects in the deviation of techniques from the average production function or efficiency frontier is rejected in favour of fixed as well as random effect deviations. The random effects model of inter-firm efficiency differences is rejected in favour of the fixed effects model only in three out of seven industries for which efficiency frontiers have been estimated. However, a regression of scores of efficiency obtained from either model on firm size and firm age over the full sample of firms shows scores increase in size as well as age, until some age threshold is reached beyond which they continue to increase with size but decrease with age.

The result that scores of efficiency increase in size confirms an earlier finding of Pitt and Lee (1981) for a sample of Indonesian weaving firms and Martin and Page (1983) for a sample of Ghanaian firms. Our finding of a positive age effect on efficiency confirms another result of Martin and Page which has also been reported by Haddad (1993) for a sample of Moroccan manufacturing firms.[22] However, there is a major point of departure between the three studies and ours. This is our finding: that firm age and firm size mainly proxy for the influence of entrepreneurial human capital and location variables in the regression of technical efficiency on firm characteristics. We find that the addition of owner human capital or firm location variables to firm size and age or vice versa in efficiency score regression does not significantly add to the explanatory power of the model. On the other hand, a regression of scores of efficiency on firm size and firm age only has a highly significant explanatory power, which is comparable to that of a separate regression of scores on human capital and location variables only.

We have also reported that location is a significant determinant of firm level efficiency. However, it is far less important than owner human capital variables. In assessing the relative importance of

[22]It should be noted, though, that Haddad's study does not directly control for size effects in relating efficiency scores to firm age. His results are therefore comparable to the other two and ours only in as far as the other explanatory variables he included are sufficiently correlated with firm size but not age.

the latter we have considered a wider range of possible indicators of entrepreneurial human capital than any previous study of firm level efficiency. Some of these represent variables which have never been included in a previous study that I am aware of, but are so important a determinant of efficiency that earlier estimates of the effect of more conventional variables might well be biased. The new variables include: family background indicators of the owner; the ethnicity of the owner; and his or her membership to business networks. We find that the last two sets of variables are significant sources of inter-firm efficiency differences in Ethiopia's manufacturing industries, although years of formal schooling of the owner is a far stronger influence. On the other hand, there is no evidence that efficiency is affected by the age of the owner, the length of his or her prior experience in the current industry, the vocational training of the owner or his or her occupational following of parents.

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Table 1
OLS Parameter Estimates of CSIZE = $\alpha + \alpha_1$ PUBLIC + βSIZE + γAGE + ϵ
1989-93; 1989-91; 1991-93; full sample*

Period of Growth	Parameters: α_0	α_1	β	γ	Adj. R^2	LM test statistic for heteroscedasticity: χ^2	N
1989-93	0.831 (0.221)	0.655 (0.196)	0.834 (0.066)	-0.111 (0.007)	0.86	24.379	159
1989-91	0.303 (0.149)	0.055 (0.155)	0.937 (0.003)	-0.078 (0.05)	0.94	16.432	159
1991-93	0.576 (0.147)	0.997 (0.278)	0.735 (0.006)	-0.066 (0.053)	0.84	23.055	194

* White's standard errors in parentheses.

Table 2
Mean and Standard Deviation of Production Function Variables:
Pooled Data; 1989, 1991 and 1993.

Industry	Mean (Standard Deviation)			Number of Observations
	OUTPUT	LABOUR	CAPITAL	
Bakery Products: (SIC 1541)	11.59 (1.57)	10.06 (1.01)	8.17 (1.44)	38
Furniture (SIC 3610)	11.18 (2.03)	10.35 (1.14)	7.69 (2.31)	29
Garment (SIC 1810)	11.37 (2.09)	9.84 (1.72)	6.78 (2.18)	66
Knitting (SIC 1730)	10.74 (1.79)	9.55 (0.96)	5.92 (2.54)	55
Leather Products (SIC 1920)	12.20 (2.20)	10.73 (1.53)	7.68 (2.42)	60
Structural Metal (SIC 2811)	11.79 (1.92)	9.96 (1.33)	8.06 (1.92)	30
Other	12.90 (2.25)	10.89 (1.74)	9.07 (2.33)	123

Table 3

Descriptive Statistics of Variables Used in Efficiency Score Regression.

Variable	Mean	Standard Deviation
Efficiency Scores:		
FIXED	7.32	4.06
SCOREF	0.00	0.98
PANU	1.71	1.35
DPANU	0.14	1.33
Firm Characteristics:		
LNSIZE	2.83	1.78
LNAGE	2.54	1.03
AGESQ	7.50	4.35
Location Variables:		
GOVRENT	0.24	0.43
OWPREM	0.51	0.50
SURROUND	0.34	0.47
Human Capital Variables:		
Education/Training:		
PRIMARY	0.27	0.45
SECOND	0.43	0.50
COLLEGE	0.17	0.37
VOCATION	0.23	0.42
APPRENT	0.52	0.50
LNEXPER	1.46	1.23
Family Background Variables:		
OWNBUS	0.31	0.47
PRIEMP	0.01	0.07
PUBEMP	0.14	0.34
Business / Social Network Variables:		
FELLOW	0.27	0.45
LNWEALTH	11.92	6.68
OTHERBUS	0.35	0.48
Ethnicity:		
AMHARIC	0.38	0.49
GURAGE	0.34	0.37
Industry Dummy Variables:		
BAKERY	0.10	0.30
FURNITUR	0.07	0.26
GARMENT	0.15	0.35
KNITTING	0.11	0.31
LEATHERF	0.14	0.34
METALWOR	0.09	0.28

Table 4

OLS Parameter Estimates of Industry Average Production Function;
Pooled Data, 1989, 1991 and 1993. Dependent Variable = OUTPUT.*

	INDUSTRY						
	Bakery Products (SIC 1541)	Furniture (SIC 3610)	Garment (SIC 1810)	Knitting (SIC 1730)	Leather Products (SIC 1920)	Structural Metal Products (SIC 2811)	Other
Constant	-0.1907 (1.689)	-4.1505 (1.923)	3.2095 (1.011)	0.1062 (1.921)	0.9950 (0.9897)	1.4737 (1.4460)	2.0548 (0.7032)
LABOUR	0.9667 (0.1987)	1.4242 (0.1070)	0.6212 (0.1490)	0.9713 (0.2389)	0.7520 (0.1194)	0.6378 (0.2025)	0.7174 (0.1036)
CAPITAL	0.2526 (0.1393)	0.0787 (0.070)	0.3018 (0.1174)	0.2289 (0.0899)	0.4083 (0.0754)	0.4912 (0.1407)	0.3347 (0.0774)
Returns to Scale	1.2193	1.5025	0.923	1.2002	1.1603	1.129	1.0527
R^2	0.60	0.73	0.61	0.63	0.79	0.75	0.74
Adj R^2	0.57	0.71	0.60	0.61	0.78	0.73	0.73
Log likelihood	-53.23	-42.17	-110.74	-82.42	-84.82	-41.16	-192.2
n	38	29	66	55	60	30	123

Table 5

Maximum Likelihood Estimation of the Random Effects Frontier Production Function (Model IIA) By Industry: Panel Data for 1989, 1991 and 1993. Dependent Variable = OUTPUT

	INDUSTRY						
	Bakery Products (SIC 1541)	Furniture (SIC 3610)	Garment (SIC 1810)	Knitting (SIC 1730)	Leather Products (SIC 1920)	Structural Metal Products (SIC2811)	Other
Constant	0.4807 (2.440)	0.2405 (4.932)	3.989 (1.075)	0.5441 (2.553)	2.0148 (1.375)	1.9180 (1.858)	3.5499 (0.9723)
LABOUR	1.0325 (0.2963)	1.5153 (0.3005)	0.6619 (0.1765)	1.0080 (0.3393)	0.7146 (0.1558)	0.7442 (0.2951)	0.9842 (0.1209)
CAPITAL	0.2037 (0.1685)	0.3583 (0.2359)	0.2725 (0.1526)	0.1944 (0.1449)	0.4094 (0.960)	0.2725 (0.2897)	0.0092 (0.097)
σ_u^2	0.2615	0.4566	0.8325	1.8720	1.4436	0.6648	0.3151
σ_v^2	0.3628 (0.1569)	0.5715 (0.1899)	1.0832 (0.1564)	0.9224 (0.1796)	0.7854 (0.1586)	0.7746 (0.528)	0.7987 (0.1658)
λ	3.8243 (2.410)	2.1902 (0.3091)	1.2144 (0.6925)	0.5342 (0.4441)	0.6927 (0.2411)	1.5041 (2.258)	3.174 (1.596)
LR test statistic of $\lambda=0$	1.51	6.96	12.59	12.64	18.26	18.04	43.20
Log-likelihood	-52.48	-44.01	-117.034	-88.74	-93.95	-50.18	-213.80
N	19	14	29	21	27	30	62

Table 6

Feasible GLS Estimation of the Random Effects Average Production Function Model (Model IIB) By Industry: Panel Data for 1989, 1991 and 1993; Dependent Variable = OUTPUT.

	INDUSTRY						
	Bakery Products (SIC 1541)	Furniture (SIC 3610)	Garment (SIC 1810)	Knitting (SIC 1730)	Leather Products (SIC 1920)	Structural Metal Products (SIC 2811)	Other
Constant	-0.3977 (1.770)	-3.5667 (2.207)	3.3715 (1.080)	-0.079 (0.1870)	1.0701 (1.040)	1.6897 (1.422)	2.5856 (0.7950)
LABOUR	1.0845 (0.2031)	1.4096 (0.2514)	0.6199 (0.1542)	1.0071 (0.2286)	0.7511 (0.1257)	0.5759 (0.2012)	0.6189 (0.1190)
CAPITAL	0.1339 (0.1354)	0.0172 (0.1456)	0.2859 (0.1203)	0.2036 (0.0908)	0.3982 (0.0798)	0.5376 (0.1459)	0.39095 (0.0911)
Returns to Scale	1.2184 (0.2436)	1.4268 (0.2049)	0.9058 (0.4578)	1.2107 (0.1780)	1.1493 (0.0917)	1.1135 (0.1896)	1.010 (0.5768)
σ_u^2	0.7792	0.8496	0.6153	0.3607	0.2895	0.3947	0.8729
σ_v^2	0.6283	0.8406	0.3513	0.3333	0.9813	0.9407	0.8026
R^2	0.59	0.72	0.61	0.63	0.79	0.74	0.73
LM test statistic against Model I	15.84	***	3,421,745.0	80.01	1,132,534.00	2,268,868.87	2,450,607.80
Hauseman Test against Model III	5.12	2.37	1.86	8.58	3.27	1.42	7.73

Table 7

Estimation of the Fixed Effects Model (Model III) By Industry:
Panel Data for 1989, 1991 and 1993; Dependent Variable = OUTPUT.

	INDUSTRY						
	Bakery Products (SIC 1541)	Furniture (SIC 3610)	Garment (SIC 1810)	Knitting (SIC 1730)	Leather Products (SIC 1920)	Structural Metal Products (SIC 2811)	Other
LABOUR	0.4741 (0.4514)	1.8235 (0.6813)	0.4469 (0.3767)	0.8087 (0.3260)	0.8187 (0.5475)	0.5168 (0.3189)	1.056 (0.2551)
CAPITAL	0.3385 (0.2536)	-0.6230 (0.4420)	0.2445 (0.4106)	0.7732 (0.3457)	0.3126 (0.2507)	0.1212 (0.5549)	0.2005 (0.2612)
Returns to Scale	0.8126 (0.2408)	1.2005 (0.5878)	0.6914 (0.1072)	1.5819 (0.4938)	1.1313 (0.4825)	0.638 (0.514)	1.257 (0.2824)
R^2	0.94	0.93	0.85	0.84	0.90	0.92	0.95
Adj. R^2	0.87	0.85	0.73	0.72	0.82	0.79	0.87
Log-likelihood	-16.66	-22.31	-78.03	-59.83	-61.44	-24.02	-95.53
LR test statistic against Model I	73.15	39.74	65.42	45.17	46.79	34.28	193.121
N	19	14	29	21	27	17	62

Note : Standard errors in parentheses

Table 8

Regression of Scores of Technical Efficiency On Firm Age and Firm Size;
All Private Firms

	Dependent Variable			
	FIXED	SCOREF	PANU	DPANU
Constant	6.8113 (0.4327)	-1.7109 (0.2323)	-2.8166 (0.3751)	-0.6725 (0.3723)
LNAGE	0.7028 (0.3776)	0.3726 (0.1027)	0.4610 (0.3415)	0.5337 (0.3390)
AGESQ	-0.1648 (0.0919)	-0.0895 (0.049)	-0.1477 (0.083)	-0.1604 (0.083)
LNSIZE	0.7873 (0.7333)	0.4315 (0.0394)	0.1725 (0.063)	0.1754 (0.0626)
BAKERY	0.4101 (0.3642)	0.3903 (0.1955)	0.5892 (0.3328)	0.0756 (0.3303)
FURNITUR	-12.5312 (0.4148)	0.1464 (0.2227)	0.4998 (0.3812)	-0.3081 (0.3784)
GARMENT	-0.4454 (0.3189)	0.44032 (0.1712)	0.6266 (0.2899)	0.0265 (0.2878)
KNITTING	-1.2344 (0.3598)	0.6549 (0.1932)	1.4347 (0.3273)	0.1846 (0.3249)
LEATHERF	-6.4476 (0.3176)	0.0805 (0.1705)	1.099 (0.2895)	-0.047 (0.2874)
METALWOR	-2.6541 (0.3854)	0.5144 (0.2069)	0.8346 (0.3514)	-1.4025 (0.3488)
R^2	0.89	0.47	0.16	0.14
Adj. R^2	.87	0.44	0.12	0.10
N	125	125	125	125

Note : Standard errors in parentheses.

Table 9

Regression of Scores of Technical Efficiency On Firm Characteristics including Firm Age and Firm Size; All Private Firms.

	Dependent Variable					Dependent Variable			
	FIXED	SCOREF	PANU	DPANU		FIXED	SCOREF	PANU	DPANU
constant	6.5985 (1.2451)	-1.9852 (0.6852)	-1.944 (1.1837)	-0.1839 (1.1361)	PUBEMP	0.4908 (0.3275)	0.3432 (0.1802)	0.5612 (0.3321)	0.6696 (0.3188)
LNAGE	-0.2756 (0.4711)	-0.2533 (0.2593)	-0.1275 (0.4677)	-0.0724 (0.4489)	FELLOW	-1.2536 (0.2573)	-0.7147 (0.1416)	-1.0776 (0.2654)	-1.0676 (0.2547)
AGESQ	0.0151 (0.1137)	0.0171 (0.0626)	0.0719 (0.1146)	-0.0761 (0.11)	LNWEALTH	0.06 (0.0955)	0.0575 (0.0525)	0.0328 (0.0955)	0.0586 (0.0917)
LNSIZE	0.7304 (0.1498)	0.3910 (0.824)	0.0635 (0.1538)	0.0284 (0.1476)	OTHERBUS	0.4448 (0.229)	0.3193 (0.126)	0.4386 (0.2295)	0.4228 (0.2203)
SURROUND	0.3811 (0.2320)	0.3099 (0.1277)	0.0486 (0.0172)	-0.0496 (0.2204)	AMHARIC	-0.5569 (0.2676)	-0.3848 (0.1473)	-0.5306 (0.2759)	-0.6418 (0.2648)
OWPREM	-0.4498 (0.2295)	-0.2674 (0.1263)	-0.052 (0.2377)	0.0171 (0.2281)	GURAGE	-0.134 (0.2998)	-0.1932 (0.165)	-0.0733 (0.31)	-0.039 (0.2976)
GOVRENT	0.5883 (0.2867)	0.2781 (0.1578)	0.3493 (0.2894)	0.4131 (0.2778)	BAKERY	0.6030 (0.3914)	0.4402 (0.2154)	0.4595 (0.4006)	-0.0966 (0.3845)
PRIMARY	1.5339 (0.4361)	0.9371 (0.24)	0.8799 (0.4001)	1.0571 (0.3849)	FURNITUR	-12.0616 (0.4187)	0.3869 (0.2304)	0.7070 (0.4272)	-0.0984 (0.4106)
SECOND	1.2552 (0.4318)	0.7075 (0.2376)	0.465 (0.1704)	0.6454 (0.3827)	GARMENT	-0.3187 (0.3829)	0.5160 (0.2107)	0.4081 (0.3917)	-0.2069 (0.376)
COLLEGE	1.7837 (0.4853)	0.9722 (0.2671)	0.7141 (0.2063)	0.9087 (0.4403)	KNITTING	0.0738 (0.4082)	1.1690 (0.2246)	1.5551 (0.4174)	0.2977 (0.4001)
VOCATION	-0.0788 (0.2664)	-0.0378 (0.1466)	0.7141 (0.4587)	0.1534 (0.2628)	LEATHERF	-6.126 (0.3454)	0.1753 (0.1901)	1.3125 (0.348)	0.2073 (0.334)
APPRENT	-0.0886 (0.2641)	-0.0273 (0.1454)	-0.3093 (0.2613)	-0.2970 (0.2508)	METALWOR	-2.4833 (0.4253)	0.5525 (0.2341)	0.5698 (0.4374)	-1.7183 (0.4199)
LNEXPER	-0.0863 (0.1072)	-0.0455 (0.059)	-0.1182 (0.1056)	-0.1554 (0.1014)	R^2	0.94	0.59	0.43	0.48
OWNBUS	-0.555 (0.2593)	-0.1976 (0.1427)	0.2548 (0.2586)	-0.2529 0.2483	Adj. R^2	0.93	0.49	0.29	0.36
PRIEMP	-1.0762 (1.1996)	-0.4706 (0.6602)	-2.2302 (1.2443)	-2.0264 (1.1944)	N	125	125	125	125

Table 10

Regression of Scores of Technical Efficiency On Firm Characteristics excluding Firm Age and Firm Size; All Private Firms.

	Dependent Variable					Dependent Variable			
	FIXED	SCOREF	PANU	DPANU		FIXED	SCOREF	PANU	DPANU
constant	6.2620 (1.3608)	-2.1673 (0.7486)	-1.6445 (1.2036)	0.1150 (1.1524)	LNWEALTH	0.16057 (0.0945)	0.0941 (0.052)	-0.0681 (0.0856)	-0.0387 (0.0819)
SURROUND	0.31084 (0.254)	0.2759 (0.1397)	0.1008 (0.2341)	0.0643 (0.2242)	OTHERBUS	0.2868 (0.2473)	0.2226 (0.1361)	0.4087 (0.2321)	0.4033 (0.2222)
OWPREM	-0.2536 (0.2438)	-0.1586 (0.1341)	0.2312 (0.2861)	0.0807 (0.2242)	AMHARIC	-0.6754 (0.2933)	-0.4516 (0.1613)	-0.5461 (0.2813)	-0.6501 (0.2693)
GOVRENT	0.833 (0.3068)	0.3903 (0.1688)	0.2312 (0.2861)	0.2952 (0.274)	GURAGE	0.0465 (0.3273)	-0.1005 (0.1801)	-0.1052 (0.3149)	-0.0762 (0.3015)
PRIMARY	1.4686 (0.4585)	0.9071 (0.2522)	1.014 (0.3967)	1.1884 (0.38)	BAKERY	0.5858 (0.4301)	0.4272 (0.2366)	0.4327 (0.4093)	-0.1174 (0.3919)
SECOND	1.3084 (0.4408)	0.7685 (0.2425)	0.7704 (0.3788)	0.932 (0.3627)	FURNITUR	-11.971 (0.4394)	0.4255 (0.2417)	0.7686 (0.4177)	-0.0344 (0.3999)
COLLEGE	1.9521 (0.5003)	1.1029 (0.2752)	1.0574 (0.4402)	1.2262 (0.4215)	GARMENT	-0.5576 (0.4143)	0.3773 (0.2279)	0.3631 (0.3929)	-0.233 (0.3762)
VOCATION	0.2352 (0.2841)	0.1407 (0.1563)	-0.2017 (0.2703)	0.188 (0.2588)	KNITTING	0.1091 (0.4488)	1.1797 (0.2469)	1.4652 (0.4262)	0.2128 (0.4081)
APPRENT	-0.2162 (0.279)	-0.1296 (0.1535)	-0.5363 (0.2544)	-0.502 (0.2436)	LEATHERF	-5.6017 (0.3542)	0.4652 (0.1949)	1.4154 (0.3326)	0.2855 (0.3184)
LNEXPER	-0.069 (0.1171)	-0.0302 (0.0644)	-0.0756 0.1071	-0.1167 (0.1025)	METALWOR	-2.6005 (0.4634)	0.5048 (0.255)	0.6718 (0.4442)	-1.6146 (0.4253)
OWNBUS	-0.3301 (0.2784)	-0.0873 (0.1532)	-0.2656 (0.26)	-0.2796 (0.2488)	R^2	0.93	0.49	0.38	0.44
PRIEMP	-1.4462 (1.3018)	-0.628 (0.7161)	-1.8037 (1.2547)	-1.6012 (1.2013)	Adj. R^2	0.91	0.38	0.25	0.32
PUBEMP	0.5682 (0.3435)	0.3375 (0.1889)	0.3078 (0.3258)	0.4328 (0.312)	N	125	125	125	125
FELLOW	-1.2526 (0.2794)	-0.6951 (0.1537)	-0.9537 (0.268)	-0.9509 (0.2566)					