Does human capital endowment of FDI recipient countries really matter?

Evidence from cross-country firm level data*

Sumon Kumar Bhaumik
Aston Business School, Aston University, UK &
IZA – Institute for the Study of Labor, Bonn, Germany
s.bhaumik@aston.ac.uk

Ralitza Dimova**
IDPM, University of Manchester, UK
IZA – Institute for the Study of Labor, Bonn, Germany
ralitza.dimova@manchester.ac.uk

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** *Corresponding author*. Institute for Development Policy and Management, School of Environment and Development, The University of Manchester, Oxford Road, Manchester, M13 9PL, United Kingdom. Phone: +44 161 275-0818. Email: ralitza.dimova@manchester.ac.uk.

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Abstract:

The stylized literature on foreign direct investment suggests that developing countries should invest in the human capital of their labour force in order to attract foreign direct investment. However, if educational quality in developing country is uncertain such that formal education is a noisy signal of human capital, it might be rational for multinational enterprises to focus more on job-specific training than on formal education of the labour force. Using cross-country data from the textiles and garments industry, we demonstrate that training indeed has greater impact on firm efficiency in developing countries than formal education of the work force.

Keywords: Human capital; Training; Firm-level efficiency; Multinational enterprises

JEL classification: F23, I25

1. Introduction

It is now stylised in the literature on foreign direct investment (FDI) that a country's stock of human capital is one of the most important determinants of its inward FDI flow (Noorbakhsh et al. 2001). A related literature suggests that FDI inflow can, in turn, augment a recipient country's human resources (Enderwick, 1985; UNCTAD, 1999). It motivates the local work force to invest in education, and, at the same time, transfers knowledge about technology and processes to a section of this work force. However, available evidence suggests that the impact of training programmes of multinational enterprises (MNEs) on the human capital development of the local labour force may have been overstated. Arguably, MNEs provide firm-specific training that increases the efficiency of their work force, without necessarily significantly deepening the knowledge base of the local workers, nor developing scarce skills such as managerial capabilities (Richman and Copen, 1972; UNCTAD, 1999).

A very different literature suggests that aggregate measures such as enrolment, drop-out rates and proportion of labour force with a certain level of education might not capture (indeed, overstate) the stock of human capital in a developing country. The range of problems with the quality of education, which is difficult to measure, includes absence of physical infrastructure such as classrooms and text books (World Bank, 1997), shortened school hours on account of over-enrolment (Glewwe, 2004), low educational attainment of teachers (Harbison and Hanushek, 1992), and absenteeism among teachers (Chaudhury et al., 2006). The policy debate also reflects issues such as apprehension about suitability of content of academic programmes for sustenance of economic activity. In other words, the stock of human capital is a noisy signal of labour force quality in developing countries.

This, in turn, has two implications. First, it suggests that MNEs investing in developing countries (or, broadly speaking, in countries with inadequate educational quality) should not rely on the perceived quality of the local labour force and be prepared to use targeted training to improve efficiency of their subsidiaries. Second, it suggests that developing countries aiming to attract FDI should perhaps not worry about progressively deepening the educational attainment of their labour force, and concentrate instead on ensuring that a large proportion of the labour force has some minimum level of education that can then be the base on which MNEs can build using targeted (or firm-specific) training programmes. While this combination of MNE and host country strategies may not be applicable for high-technology industries, it could be a mutually acceptable equilibrium for a wide range of low-technology industries in which most developing countries (especially low income countries) can reasonably expect FDI.

In this paper, using cross-country firm-level data from the textiles and garments industry, which is ubiquitous across developing countries and one in which developing countries arguably have comparative advantage, we examine two hypotheses, namely, that education level of the local workforce does not improve production efficiency of firms, and that MNE training significantly improves efficiency (or reduces inefficiency). Our results are consistent with these hypotheses. Using data on MNEs across a cross-section of industries, we also demonstrate that educational level of workers has the desired impact on efficiency of these firms, suggesting that, in keeping with popular perceptions, MNEs are perhaps able to cherry pick high quality labourers. While the data are fraught with problems, thereby limiting the methodological scope of our research, our results provides *prima facie* evidence about the importance of perceived human capital (or formal education) of workers in FDI recipient countries that have significant relevance for both MNE strategy in developing countries, and the education policies of developing country governments.

The rest of the paper is organised as follows: In Section 2, we discuss the stochastic frontier methodology that is used for the empirical analysis in the paper. The data and specification are discussed in Section 3, and the regression results in Section 4. Finally, Section 5 concludes.

2. Empirical strategy

It is well understood that the main sources of productivity growth at the firm level are technical progress and efficiency gains. In traditional industries such as textiles where there has been little change in technology in the recent past, and where the shift to power looms took place decades ago even in developing countries (Bhaumik, Gangopadhyay and Krishnan, 2008), productivity growth is driven largely by changes in efficiency (Margono and Sharma, 2006). Efficiency, in turn, is affected by an increase in the human capital endowment of workers: *ceteris paribus*, more can be produced with the same number of workers, or the same amount can be produced using fewer workers. Hence, in the context of our analysis, a key issue is how formal education of the workforce and training offered by the companies that employ them affect firm level efficiency. Our hypothesis is that efficiency will be increased by training, and will be unaffected by the formal education levels of the work force.

The impact of firm characteristics such as formal education of workers and training on efficiency can be examined using stochastic frontier models. The neo-classical production theory implicitly assumes that all production activities are on the frontier (defined either as the maximum possible output that is technically attainable given inputs (output-oriented measure), or that the observed output level can be produced using lesser inputs (input-oriented measure) of the feasible production set (subject to random errors). The production efficiency literature, however, relaxes the assumption, and considers the possibility that producers may operate below the frontier due to technical inefficiency (Kumbhakar and Lovell, 2000). A production plan is *technically inefficient* (output-oriented) if actual output produced is less than the frontier output (subject to random errors). Alternatively, if inputs actually used is more than the minimum required to produce a given level of output the production plan is said to be *technically inefficient* (input-oriented).

Mathematically, a production plan with input-oriented (IO) technical inefficiency is written as

$$y = f(x\exp(-\eta)), \quad \eta \geq 0 \tag{1}$$

where η measures IO technical inefficiency (TI), and exp(-η) measures IO technical efficiency (TE). For small η, exp(-η) can be approximated by 1 -η. Thus, we get the following familiar relationship, TE = 1 - TI. A mathematical formulation of output-oriented (OO) technical inefficiency is

$$y = f(x)\exp(-u), \quad u \geq 0 \tag{2}$$

where *u* measures OO technical inefficiency. Again for small *u* we can approximate exp(-*u*) by 1-*u*, which gives us the familiar result, TE = exp(-*u*) = 1 - *u* = 1 - TI.

Since inefficiency can be viewed either in the input or output direction, we get the following relationship between the two measures, viz., $f(x)\exp(-u)$ = $f(x.\exp(-\eta))$. If the production function is homogeneous of degree *k* then $\eta.k = u$, i.e, OO inefficiency is a constant multiple of IO inefficiency. In the special case when return to scale is unity, both inefficiency measures are the same. If return to scale is neither constant nor unity, the relationship is more complicated (although exact and is given by $f(x)\exp(-u)$ = $f(x.\exp(-\eta))$) and it depends on the input quantities.

Earlier empirical studies on determinants of firm efficiency typically used stochastic frontier models to estimate firm-level efficiency, and then followed it up with an ordinary least square regression model in which efficiency was regressed on firm-level and contextual variables. However, as argued by Kumbhakar et al. (1991), estimates generated by this two-stage methodology are inefficient because the assumption of independence of the inefficiency effects in the two stages is typically violated. They propose an alternative approach in which *u* is explicitly modelled as a vector of explanatory variables and a random error. Battese and Coelli (1995) propose a model that is an equivalent of the Kumbhakar et al. (1991) specification:

$$y = X\beta + (v - u) \tag{3}$$

$$m = Z\delta \tag{4}$$

where *X* is a vector of variables that determine output and *Z* is a vector of variables that influence the efficiency of a firm. The two equations are estimated simultaneously, thereby eliminating the aforementioned inefficiency problem. Note that in case of a production function *m* would measure inefficiency whereas in case of a cost function it would measure efficiency.

In our paper, we adopt the Battese and Coelli (1995) approach to modelling output and efficiency. We model output as a function of material inputs, labour and capital, and simultaneously model firm level inefficiency as a function of human capital of the work force, training, and indicators of labour market institutions. If formal education of workers in developing countries is indeed a noisy signal of human capital, then we should find that training reduces firm level inefficiency much more than formal measures of human capital of workers (such as years of education). In the limit, only training should have a significant (and negative) impact on firm level inefficiency.

2.1 Endogeneity of training

It has been argued in the literature on training that it is endogenous to firm characteristics (Blundell, Dearden and Meghir, 1996). At the individual level, endogeneity might arise from the fact that individual labourers are not randomly chosen for training, but that this decision is based on unobserved characteristics of these labourers. At the aggregate (or firm) level, it might arise from the fact that training is either related to overall characteristics of labourers, such as their skill level, or to outcomes such as firm performance. In particular, firms are more likely to introduce human resource practices such as training when they are in trouble or when their productivity is below industry average (Bartel, 1994; Black and Lynch, 2001). Dearden, Reed and Van Reenen (2000) argue that ignoring this endogeneity leads to an *underestimation* of the impact of training.

Where panel data are available, researchers have attempted to correct for this endogeneity using the GMM estimator. However, the use of the GMM estimator does not necessarily alter the economic implications of the results in a significant way. For example, in Dearden, Reed and Van Reenen (2006), the coefficient estimate for the impact of training on log value added per worker is 0.70-0.78 when the random effects estimator is used, and the coefficient estimate is 0.60 when GMM is used. At the same time, as discussed by Zwick (2006), past values of training might be weak instruments of current decisions about training (and its intensity), with attendant implications for GMM estimation, and an alternative is the use of stylized instrumental variable (IV) estimation whereby the incidence (or intensity) of training is regressed on a set of determinants that includes some instruments, and then the predicted value of the likelihood (or intensity) is used in the second stage regression that estimates the impact of training on, among others, productivity.

In the context of our paper, given the cross-section nature of the data, the use of the GMM estimator, irrespective of its advantages and disadvantages, is infeasible. If we have to correct for potential endogeneity of the training variable, we therefore have to adopt the IV approach. However, this, in turn, leads to the well understood problem about the trade off between the unbiasedness and inefficiency of IV estimators. Since good (and strongly exogenous) instruments are not easily found in academic work, a rule of thumb involves the use of the mean squared error (MSE) criterion to trade off between unbiasedness and inefficiency. The MSE criterion suggests that use of the IV estimator may not always be desirable (Bartels, 1991), and it is indeed sometimes abandoned in favour of ordinary least squares (OLS) and other non-IV estimators (e.g., Bhaumik and Nugent, 1999).

We estimated a probit model in which the dependent variable is training (which, as we shall see later, is a dummy variable). The explanatory variables included change in assets, change in average education of the labour force, change in value added and exports as a share of total sales,[1] which are consistent with the argument that HR practices like training are introduced as a reaction to changes in a firm's performance or as a reaction to a problem with the quality of its resources. The regression estimates, not reported in the paper, suggest that while some of the explanatory variables have meaningful coefficient estimates -- training is less likely in companies that experience growth in assets and in those for which exports account for a high proportion of sales, the IV regression overall is very weak, with pseudo R-square values of less than 0.05. This, in turn, suggests that the use of the IV approach in our case would result in significant loss of efficiency, and indeed would not be meaningful, given the weakness of the IV regression model. We, therefore, do not instrument the incidence of training in the rest of the paper.

3. Data and specification

3.1 Data

Our main data source is the World Bank Enterprise Surveys, which contain firm level data from approximately 100 less developed and transition economies. Aside from containing the usual for such type of data set balance sheet and financial statements information, which allow us to estimate production function for a number of different sectors, the dataset also contains information on various workers characteristics, such as the proportion of the workforce in different education categories, as well as information on whether this workforce has received any training by the firm for which it works. We also have information on both foreign ownership and the access to foreign technology. We complement this data with measures of institutional characteristics of labour market from the Botero et al. (2004) dataset.

[1] The data includes information about the 1-period past values of assets, educational level of labourers, and value added. Hence, we were able to compute these changes.

The main disadvantage of our dataset is that missing data significantly limits number of observation for individual industrial sectors. The number of observations is especially limited for firms that are predominantly foreign owned. Missing values have affected our analysis in two ways. First, after accounting for missing values for key variables such as capital and materials, only the textile and garments sector has adequate number of observations to estimate our production and inefficiency equations.[2] Second, in some cases, we were required to use dummy variables instead of continuous variables; e.g., a large number of missing values for the variables that measures the proportion of employees who have received training, we have had to use a cruder measure of training involving the use of a dummy variable.

As we shall see later in the paper, while this restricts the scope of our empirical analysis, it nevertheless yields interesting observations that have significant implications for human resource (training) strategies of MNEs, education policies of developing countries seeking to attract FDI, and the ease with which training provided by MNE subsidiaries to their work force can have spillover effects.

3.2 Specification

To begin with, we consider the stylised Cobb-Douglas production function

$$Y = A.M^{\alpha}L^{\beta}K^{\gamma} \tag{5}$$

where Y is total sales, M is the dollar value of "materials" (i.e., non-labour and non-capital inputs), L is the dollar value of labour inputs, K is the capital stock, and A is a measure of technology which, in our case, is a dummy variable that takes the value one if a firm has access to foreign technology. The Cobb-Douglas production function yields the familiar log-linear production function. We later use the more general translog functional form for the production function. We model firm level inefficiency as a function of the following (sets of) variables:

Educational attainment of the labour force. The data provides information on proportion of the work force that have fewer than 6 years of education, between 6 and 9 years of education, between

[2] As indicated at the outset, restricting our analysis to the textile and garments sector is conceptually not a major problem, given that this is a key sector in developing/emerging economies.

9 and 12 years of education, and more than 12 years of education. However, information about the two middle categories is largely missing, and hence unusable. Further, while it is reasonable to assume that firm level inefficiency increases with the proportion of workers with fewer than 6 years of education and decreases with the proportion of workers with more than 12 years of education, it is difficult to form *a priori* expectations about the impact of the middle education categories on inefficiency. Hence, in our specification, we include the proportion of the work force with the lowest and highest recorded levels of education.

Non-technological aspects of foreign ownership. The stylised literature on MNEs suggests that these firms have innate capabilities that are a key driver of their overseas investment decisions, and the popular wisdom is that these innate capabilities are generally superior technologies or production processes. In our stochastic frontier formulation, this aspect of MNEs is included in the production function, such that any indicator of the multinationality of the firm – a dummy variable in our case – captures non-technical aspects of foreign ownership. Specifically, it can capture the so-called liability of foreignness (for details about the literature, see Miller and Parkhe, 2001), one aspect of which is the difficulty experienced by foreign owners as they grapple with very different organisational cultures in overseas locations (Brouthers et al., 2003).

Training. We distinguish between the training provided by MNEs and local firms by including in the inefficiency equation an indicator of training – a dummy variable in our case, both on its own and in interaction with the dummy variable that indicates foreign ownership.

Local labour market institutions. Since labour market institutions such as flexibility with respect to hire and fire may affect allocational efficiency and x-efficiency of firms, we include in the specification the indices of labour market institutions reported by Botero et al. (2004). While the years of survey for individual countries vary between 2002 and 2006, we make the reasonable assumption that labour market institutions in countries do not change rapidly, such that the Botero et al. indices capture the nature of labour market institutions in these countries to a reasonable extent.

4. Results and discussion

In Table 1, we report the estimates for the Cobb-Douglas production function and the inefficiency equation. We start with an estimation of the production function itself (column 1), and gradually add explanatory variables to the inefficiency equation (columns 2-5). In Table 3, we report the coefficient estimates of the inefficiency equation alone, for the more general translog production function; columns 2a-5a in Table 2 correspond to columns 2-5 of Table 1. Table 2, therefore, provides a robustness check for Table 1., and since the results reported in Table 3 are indeed consistent with those in Table 2 we discuss only the results discussed in Table 2.

The coefficient estimates of the production function reported in Table 1 suggest that the textiles and garments industry enjoy increasing returns to scale, albeit marginally. The coefficient of the foreign technology dummy is significant for the jointly estimated production-inefficiency model (columns 2-5), strongly for the (nearly) fully specified models in columns 4 and 5. The coefficient of the technology variable (0.25) too is comparable to those of the factor inputs. Hence, even for a relatively low technology industry such as textiles and garments, technology can have a significant and economically meaningful impact on output. Note, however, that our measure of foreign technology merely indicates that a firm has access to this technology, and does not limit the access to foreign technology only to MNE subsidiaries. In other words, the same outcome can be generated if domestic firms in the host countries can procure foreign technology through purchase of state of the art capital equipment, technology licensing, etc.

The coefficient estimates of the inefficiency equation suggest the following:

- *Number of years of schooling may not capture the quality of education and skill of the labour force in developing countries*. Note that the inefficiency level *increases* with the proportion of the work force with more than 12 years of education. This could, of course, imply that many of these workers are not involved in productive activities, e.g., there could be administrative and managerial staff who do not add significantly to the production process. However, while the data do not permit us to examine this more closely, our counterintuitive result is certainly consistent with the literature on the problems associated with the measurement of quality of education and skill of the labour force in developing countries.

- *Foreign owned firms may indeed suffer from liability of foreignness.* This is consistent with the observation that the foreign ownership dummy has a *positive* impact on inefficiency. To recapitulate, we already have a proxy for foreign technology in the production function. Hence, the foreign ownership dummy variable in the inefficiency equation captures non-technology factors such as cultural distance.
- *MNE subsidiaries in developing countries benefit significantly by providing training to their work force*. Note that training in general does not reduce inefficiency. Indeed, in column 5, the training dummy variable has a *positive* coefficient, indicating that training provided by domestic firms may actually increase inefficiency. However, training provided by MNE subsidiaries not only reduces inefficiencies, it also has a much greater impact on (in)efficiency than the years of schooling of the work force.
- *Labour market institutions that facilitate provision of significant social security benefits reduces inefficiency*. The labour market index with the negative and significant coefficient (column 6) captures the extent of protection provided to employees against old age, death and disability, sickness and healthcare coverage, and unemployment benefits. It is well understood that these benefits can both increase a labourer's reservation wage and can enable her to remain productive by providing protection against malnutrition and sickness, and by facilitating search and thereby enhancing x-efficiency. This is consistent with available evidence about the impact of safety nets in the labour market on firm level (in)efficiency (Bhaumik and Dimova, 2011).

In Table 3, we report the estimates of the production function and inefficiency equations for only MNEs. Restricting the sample to only MNE subsidiaries results in none of the industries having adequate number of observations for estimation of industry-specific production functions. We, therefore, estimate a single production function with cross-industry data, with controls for 2-digit industries. Further, since our results reported in Tables 1 and 2 are robust across functional form of the production function, we have used only the Cobb-Douglas functional form for this exercise. We recognise the importance of estimating production functions for individual industries. But the small samples for individual industries have also forced us to pool together MNEs from across 27 industries. We estimate a single production function for this cross-industry sample, with dummy variable controls for individual industries. While this is not ideal, and is an outcome of data limitation, we feel that our results highlight some interesting aspects of MNE investment in developing countries. The results indicate the following:

- *MNE subsidiaries in developing countries can reduce inefficiency significantly by providing training to their work force*. This is consistent with the results reported in Tables 1 and 2, discussed above.
- *Inefficiency of MNE subsidiaries decreases with the proportion of workers with higher education*. This contrasts with the results reported in Tables 1 and 2, and suggests that MNEs possibly have mechanisms to identify and cherry pick workers whose years of education accurately reflect their quality of education and skill levels.

Our results have interesting implications for education policies and impact of FDI on human capital development in developing countries. They suggest that, in general, years of education, which is a stylised metric for evaluating success of education policies in these countries, may not accurately reflect quality of education and skills of the labour force. If so, as argued earlier, MNEs would have to train their work force anyhow, such that the link between perceived human capital of the work force and inward FDI flow is weakened considerably. There is some evidence to suggest that MNEs can and do cherry pick those workers whose years of education accurately reflects their quality of education and skills. However, the magnitude of the marginal impact of formal education of workers on (in)efficiency is much less than the magnitude of the marginal impact of training, i.e., training still matters much more than the formal education of the workers.

5. Conclusion

The stylised literature has concluded that increase in human capital stock is essential for attracting FDI. The policy implication of this line of argument is that developing country that aims to attract FDI should invest in education. An implicit assumption is that the observable educational levels of workers accurately reflect the human capital stock of the workers. However, in most (if not all) developing countries, formal educational levels are a noisy signal for human capital, a fact that is often overlooked in the discussion about the linkage between human capital of workers and FDI. It is easy to argue that under such circumstances efficiency and productivity of MNE subsidiaries are more likely to depend on firm-specific training of workers than on their formal educational levels. In this paper, using cross-country firm-level data for the textiles industry, we test this hypothesis.

Our results suggest that, at least for industries in which developing countries have comparative advantage, and yet where there is limited technical progress, this is indeed the case: training reduces inefficiency significantly but formal education level of workers does not have a significant impact of this inefficiency. The impact of training is even greater for MNE subsidiaries. Our analysis involving a cross-industry analysis of only MNE subsidiaries indicate that observable human capital of workers may reduce firm-level inefficiency, suggesting that there may be merit to the popular perception that MNEs are able to cherry pick high quality labourers. Importantly, however, even within a sample of MNE subsidiaries, training has far greater impact on firm-level (in)efficiency than formal education level of workers.

Our results bring into question the popular wisdom that significant investment in education is necessary to attract human capital. While this may be true for high technology sectors such as ICT and pharmaceuticals in which only a handful of developing countries like India have a comparative advantage, for many other industries in which developing countries have comparative advantage a level of education that enables workers to absorb firm-specific training may be sufficient to attract FDI. In other words, educational policy that aims to widen the coverage of primary and secondary education might be optimal for early stages of industrialisation that is generally based on low technology industries.

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Table 1
Determinants of inefficiency in a Cobb-Douglas production function

	(1)	(2)	(3)	(4)	(5)
Production function					
(Log) materials	0.47 *** (0.26)	0.43 *** (0.02)	0.42 *** (0.02)	0.40 *** (0.02)	0.38 *** (0.02)
(Log) labour	0.27 *** (0.02)	0.27 *** (0.03)	0.26 *** (0.03)	0.25 *** (0.02)	0.32 *** (0.03)
(Log) capital	0.31 *** (0.02)	0.33 *** (0.02)	0.33 (0.02)	0.37 *** (0.02)	0.37 *** (0.02)
Access to foreign technology (dummy)	0.10 (0.08)	0.18 * (0.09)	0.16 * (0.09)	0.29 *** (0.09)	0.25 *** (0.09)
Constant	1.24 *** (0.09)	0.99 *** (0.09)	1.01 *** (0.08)	1.24 *** (0.09)	1.04 *** (0.09)
Inefficiency equation					
Proportion of employees with less than 6 years education		0.08 ** (0.04)	0.12 *** (0.05)	0.002 (0.004)	- 0.0003 (0.005)
Proportion of employees with more than 12 years education		0.10 *** (0.04)	0.14 *** (0.04)	0.02 *** (0.003)	0.01 *** (0.003)
Foreign ownership (dummy)			- 30.71 (1142.74)	4.60 *** (1.13)	3.18 *** (1.06)
Training (dummy)				0.50 ** (0.25)	0.02 (0.27)
Foreign ownership × Training				- 2.04 *** (0.75)	- 1.51 ** (0.66)
Index for employment flexibility					1.53 (4.05)
Index for social security benefits					- 4.65 *** (1.57)
Index for collective bargaining					4.68 (5.83)
Constant		- 10.41 *** (3.82)	- 14.42 *** (4.67)	- 2.61 *** (0.53)	- 2.77 (4.89)
Log likelihood	- 1260.90	- 940.91	- 937.30	- 811.73	- 790.77
Wald chi-square Prob > |chi-square|	7623.42 (0.00)	5491.47 (0.00)	5536.37 (0.00)	5958.99 (0.00)	5758.40 (0.00)
Number of observations	1060	804	804	768	768

Note: Values within parentheses are standard errors.
***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

Table 2
Determinants of inefficiency in a translog production function

	(2a)	(3a)	(4a)	(5a)
Production function				
Translog functional form	Yes	Yes	Yes	Yes
Inefficiency equation				
Proportion of employees with less than 6 years education	- 0.006 (0.005)	- 0.005 (0.005)	- 0.0004 (0.003)	- 0.004 (0.004)
Proportion of employees with more than 12 years education	0.02 *** (0.003)	0.02 *** (0.003)	0.02 *** (0.003)	0.01 *** (0.003)
Foreign ownership (dummy)		1.23 *** (0.31)	4.64 *** (0.93)	2.70 *** (0.93)
Training (dummy)			0.51 *** (0.17)	- 0.17 (0.42)
Foreign ownership × Training			- 2.29 *** (0.62)	- 1.61 *** (0.58)
Index for employment flexibility				1.36 (3.30)
Index for social security benefits				- 6.04 *** (1.36)
Index for collective bargaining				5.99 (4.80)
Constant	- 1.36 *** (0.29)	- 1.42 *** (0.24)	- 1.98*** (0.35)	- 1.86 (3.98)
Log likelihood	- 892.22	- 886.20	- 731.57	- 679.80
Wald chi-square Prob > |chi-square|	6413.01 (0.00)	6603.14 (0.00)	8250.41 (0.00)	8602.05 (0.00)
Number of observations	804	804	768	768

Note: Values within parentheses are standard errors.
***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

Table 3
Determinants of inefficiency in multinational enterprises

	(1)	**(2)**
Production function		
(Log) materials	0.44 *** (0.03)	0.43 *** (0.03)
(Log) labour	0.32 *** (0.05)	0.33 *** (0.04)
(Log) capital	0.29 (0.04)	0.29 *** (0.03)
Constant	0.94 (0.30)	0.95 *** (0.29)
Industry controls	Yes ***	Yes ***
Inefficiency equation		
Proportion of employees with less than 6 years education	- 1.56 (1.82)	- 3.36 (7.24)
Proportion of employees with more than 12 years education	- 0.74 *** (0.28)	- 0.31 * (0.17)
Training (dummy)	- 4.90 *** (1.79)	- 4.17 *** (1.44)
Index for employment flexibility		- 142.86 (6724.60)
Index for social security benefits		- 138.99 (8092.14)
Index for collective bargaining		- 131.41 (10312.88)
Constant	8.60 *** (1.79)	180.83 (3053.39)
Log likelihood	- 237.66	- 225.13
Wald chi-square Prob > |chi-square|	1119.45 (0.00)	1190.33 (0.00)
Number of observations	221	221

Note: Values within parentheses are standard errors.
***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.