Exports and Firm-level Efficiency in African Manufacturing

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Abstract

In this paper, we use firm-level panel data for the manufacturing sector in four African countries to estimate the effect of exporting on efficiency. Measures of firm-level efficiency using stochastic production frontier models are constructed for the period 1992 to 1995. We find that there are large efficiency gains from exporting both in terms of levels and growth, and contrary to China, the gains are largest for the new entrants to exporting. We control for unobserved heterogeneity using a dynamic model with correlated random effects. Results are robust and consistently, we find evidence of a learning-by-exporting effect as well as self-selection of the most efficient firms into exporting. The effect of exporting on efficiency appears to be larger in this African sample than in comparable studies of other regions which is consistent with the smaller size of domestic markets.

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I. Introduction

Many analysts believe that trade liberalization and an export-oriented strategy increase firm-level efficiency (Krugman, 1987; Rodrik, 1988, 1991; Grossman and Helpman 1991). However, although this is supported by anecdotal evidence describing the association between exporting activities and efficiency (Nishimizu and Page, 1982; Haddad, 1993; Harrison, 1994; Aw and Hwang, 1995), there is as yet little systematic evidence that exporting *causes* efficiency gains. Indeed, causality may run in the other direction: efficient firms may self-select into the export market.

The first study analysing the causal relationship between exporting and productivity at the firm-level in the recent literature was on the U.S. economy (Bernard and Jensen, 1995, 1999). These authors find little evidence of any learning-by-exporting effect. However, since the U.S. has the largest, most competitive and most technologically advanced economy, it is the least likely to be characterised by efficiency benefits of exporting. The ideal economy in which to find efficiency effects would have the opposite characteristics. It would be small, so that exporting would offer maximum scope for reaping economies of scale. It would have high trade restrictions which would enable even its potentially tradable sectors to be uncompetitive, so that exporting would offer maximum scope for the increased discipline of competition. It would be technologically backward, so that contact with foreign customers would provide the maximum scope for learning opportunities. Our study is based on four Sub-Saharan African (SSA) countries each of which has these characteristics: Cameroon, Ghana, Kenya and Zimbabwe. The four economies are of similarly modest size, with GNP averaging only $7.7bn as of 1996. Africa has had historically the highest level of trade restrictions (Dollar, 1992; Sachs and Warner, 1997) and the four economies conformed to this pattern, with low levels of competition as a result (see Bigsten *et al.*, 1999a, for a review of the policy environments in the four countries). They have all been technologically backward, for example with low levels of human capital endowments. Thus, if exporting induces efficiency in any environment, it should do so in these economies.[1]

To date, there are only few studies examining causality issues on countries other than the USA: that of Clerides *et al*. (1998) on Mexico, Colombia and Morocco and that of Kraay (1997) on China. The characteristics of these economies lie between sub-Saharan Africa and the USA: their economies are between seven and 100 times as large as the four African economies considered here, and they are considerably more open and technologically advanced. The results of the studies are mixed. Clerides *et al*. observe that the positive association between export status and productivity is due solely to the self-selection of the relatively more efficient plants into foreign markets and find no evidence of learning-by-exporting effect, except in the apparel and leather industries in Morocco. Kraay finds that continuously exporting causes faster growth in efficiency, but that new entrants to exporting reap no early efficiency benefits. The latter result is paradoxical, since it would be expected that learning effects are at their peak when exporting starts, and gradually diminish as the firm catches up with best practice.

In this paper, we utilise comparable panel sample surveys of four sub-sectors of manufacturing covering the period 1992-95 in Cameroon, Ghana, Kenya and Zimbabwe to test the presence of learning-by-exporting and self-selection effects. Measures of plant-level efficiency using stochastic production frontier models are constructed to test the relationship between exporting and firm-level efficiency. Using simple regressions, we find that there are large efficiency gains from exporting both in terms of levels and growth, and contrary to China, the gains are largest for the new entrants to exporting. In order

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[1] There is, however, a literature which is pessimistic about the effect of exporting on African efficiency. Pack (1993) suggests that producers may be unable to respond to reforms because of weaknesses in institutions, infrastructures and the human capital base. Matin (1992) suggests that producers may choose not to respond to reforms because a history of policy reversal may have undermined their credibility. El Badawi (1992) suggests that even if producers do respond, the resulting productivity gains may be offset by declines in factor accumulation.

to more formally test whether past exports influence current efficiency level, we follow an alternative approach consistent with that of Clerides et al (1998). As these authors, we estimate the efficiency equation jointly with an export-participation equation. We specify the self-selection process using a non-linear and dynamic model with serially correlated error terms. However, whereas Clerides et al. assume the random effects to be bivariate normal, we use a more flexible approach following Heckman and Singer (1984) and use a non-parametric maximum likelihood (NPML) strategy in which the unknown distribution of the random effects is approximated by a discrete multinomial distribution.

Our NPML estimates of the participation equation yields results similar to those of Clerides et al (1998) and Bernard and Jensen (1999) with respect to the presence of self-selection, as firms with higher past efficiency are more likely to become exporters, as well as of high sunk cost of breaking into the foreign markets, as past exporters are more likely to remain active in the export market. However, contrary to these authors, we find evidence that lagged export experience is statistically significant in the efficiency equation, providing support for the learning-by-exporting hypothesis.

The paper is organized as follows. Section 2 presents the data and measures of technical efficiency. Section 3 develops the econometric methodology and test the relationship between firm-level efficiency and export history. We then estimate a dynamic system allowing for correlated random effects which we estimate using NPML. Section 4 concludes.

II. Data and Efficiency Measures

We use panel data models to investigate the association between exports and firm-level efficiency. We estimate firm-specific technical efficiency using a stochastic frontier production model. These estimates are then used to test the causal relationship between technical efficiencies and export history. First, we treat the level of efficiency as the dependent variable, following Kraay (1997) in testing whether the history of export activity explains efficiency, controlling for the past level of efficiency. Secondly, following Bernard and Jensen (1999) we treat the growth in efficiency as the dependent variable, and test whether the history of export activity explains efficiency growth. Both of these approaches suffer from the problem that they neglect unobserved heterogeneity. For example, a firm with atypically good management might be expected both to be more likely to export and to have more rapid growth in efficiency. Our third step, consistent with the approach adopted by Clerides et al (1998), is to control for unobserved heterogeneity by estimating a dynamic system with correlated nonparametric random effects.

Data

Our data are for manufacturing firms in four African countries - Cameroon, Kenya, Ghana and Zimbabwe - obtained during the period 1991 to 1995 as part of the Regional Program on Enterprise Development (RPED) coordinated by the World Bank. In each country, over a period of three years, a panel of firms in the manufacturing sector was surveyed and information was gathered on a variety of issues, including outputs and resource use. The periods covered by the surveys were as follows: for Kenya, 1992 to 1994; for Ghana, 1991 to 1993; for Zimbabwe, 1992 to 1994; and for Cameroon, 1992/93 to 1994/95. All the countries faced problems in their macroeconomic environments that had a significant impact on manufacturing sector performance. They had all adopted import substitution development policies from independence through the late 1970s. In the mid to late 1980s, they had all introduced `structural adjustment' programs with the support of the World Bank and other aid organizations, with emphasis on macroeconomic reforms, trade liberalization and privatization. The scope and success of these programs varied. For a discussion of policy in the four countries see Bigsten *et al.* (1999a, 1999b).

In obtaining econometric estimates of technical efficiency we have used the balanced panel of those firms for which observations exist for all three survey years because the reliability of our measure of technical efficiency depends crucially upon the length of the time dimension of the panel. Table A1 in the Appendix presents summary statistics on the sample. We observe significant variations in capital and labor inputs and value added both within and among countries.

Estimation of technical efficiencies

To measure firm-level productivity levels, we estimate production function frontiers and derive technical efficiency indices using fixed and random effects, and time variant productivity models.

Firm-level efficiency is often measured using the efficiency frontier approach (see surveys by Bauer, 1990; Green, 1993). In view of variations in plant-technology, the idea is to estimate actual deviations from an efficient isoquant instead of estimating the production function of a representative plant (an average production function). The frontier production technique $y=f(\mathbf{x},t)$ represents the maximum output achievable with the vector of inputs $\mathbf{x}$ at time t. The observed production of firm i will fall short of the frontier by some amount $u_i=f(\mathbf{x}_i,t)-y_i$. If the production function f(.) can be estimated, then a set of specific efficiency indexes u_i can be obtained.

Assuming a standard log-linear (Cobb-Douglas) production function and taking logs produces the production frontier model in the form proposed by Lovell, Defourny and N'Gbo (1992):

$$(1) \qquad \ln Y_{it} = \beta_0 + \beta_1 \ln L_{it} + \beta_2 \ln K_{it} + v_{it} + u_{it}$$

where Y_{it} is the observed value added of the ith firm (*i=1,.....,N*) at time t, K represents the replacement value of equipment and L the number of employees, in firm i in period t (*t=1,....,T*), and ßo, ß1 and ß2 are a vector of technology parameters to be estimated. The compound disturbance is composed of two terms. The first, v_{it}, is a random disturbance assumed to be distributed identically and independently across plants as $N(0, \sigma^2)$. It represents factors such as luck, weather conditions, and unpredicted variation in inputs. The second, u_{it}, is a firm-specific effect that reflects firm efficiency and management skills. Its distribution is one sided, reflecting the fact that output must lie on or below the frontier. u_{it} is assumed to be independently and identically distributed across plants as the non positive part of a $N(\mu , \sigma^2)$ distribution truncated above at zero. Both *v* and *u* are assumed to be distributed independently of the exogeneous variables in the model.

Potentially, it is possible to use panel data to break down changes in productivity into a technical progress component, measured by the shift in the frontier, and a technical efficiency component, measured by the change in the distance of non-frontier firms from the frontier.[2] However, the estimate of changes in technical progress is very sensitive to observational error.[3] So, rather than breaking down

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[2] This approach was first proposed by Nishimizu and Page (1982). In a log-linear form, the frontier model may be written as, $\log Y_{it} = \log(f(x_{it}, T)\exp(u_{it})$. The derivative with respect to time gives

$$(\delta \log Y_{it})/\delta T = \delta \log(f(x_{it},T))/\delta \log x_{it} . \delta \log x_{it} /\delta T + \delta \log(f(x_{it},T))/\delta T + \delta \log(\exp u_{it})/\delta T$$

The two last terms represent technological progress and efficiency gains.

[3] Indeed, it is possible for virtually all firms to increase their relative efficiency because the frontier is defined by only a single observation, namely the most productive firm. This is subject to changes in measurement error: the firm that is apparently the most productive will tend to be the one in which a combination of genuine efficiency and measurement error has made it an outlier. If measurement error falls between rounds as the survey improves, then all firms other than the frontier firm may appear to move towards the frontier, whereas the frontier itself will appear to move in. Thus, there would be a spurious tendency towards apparent technical regression (the moving inwards of the

changes in efficiency into the two components, we therefore focus only upon levels and changes in technical efficiency using a stochastic frontier model.

The stochastic production frontier is motivated by the idea that deviation from the production frontier might not be entirely under the control of the firm. Contrary to deterministic models where, for instance, bad weather or a high number of random equipment failures might appear to constitute inefficiency and translate into increased inefficiency measures, the stochastic frontier model allows for such random events (Green, 1993).[4] Furthermore, the stochastic nature of the model allows some observations to lie above the efficiency frontier, making the estimates less vulnerable to outliers, in contrast to deterministic models.

Following Aigner *et al.* (1977), Jondrow *et al.* (1982), and Battese and Coelli (1992), an estimate of the efficiency measure of the ith firm at the th time period is given by:

$$eff_{it} = \exp(\hat{u}_{it})$$

Assuming that firm-level inefficiency, u_{it}, is constant over time, equation (1) was estimated separately in each manufacturing sector in each of the four countries, using the fixed effect and random effect approaches. [5] Table A2 in the Appendix presents the estimated coefficients of the random effect estimators (GLS) [6]. The estimation results have a reasonable fit. For all countries, the most important factor is labor.

The production frontiers were then used to estimate the efficiency index. To distinguish the efficiency levels of exporters from those of non-exporters, we divided the firms into two categories, initial exporters and non-exporters. Are (say) non-exporting firms generally further from the frontier than firms which export initially? Table 1 presents average efficiency levels in the four countries over the sample period for initial exporters and non-exporters in each sector. Low technical efficiency levels in some sector might indicate unexploited opportunities for productivity improvements through learning. These results are consistent with observed significant average inefficiency in the African manufacturing sector (Pack, 1988). We observe that with Random effects average estimates over the period, exporters exhibit higher yearly average efficiency than non-exporters in all countries.

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frontier) with increased efficiency as firms converge towards the frontier.

4 Another interpretation is that each producer faces its own production frontier and that the frontier is randomly placed by the whole collection of stochastic elements which might enter the model and escape the control of the firm (Green, 1993).

5 The fixed-effect model can be estimated using a *within estimator* or least square dummy variable (LSDV) estimator. This is obtained through the addition of a dummy variable for each firm or by the ordinary least square after expressing all data in terms of deviation from the firm means. A measure of technical efficiency relative to the production frontier is in this case obtained as follows (see Green, 1993):
$\hat{\mu}_j = \overline{Y}_j - \hat{\beta}'\overline{X}_j$; and firm-effect is obtained as: $\hat{u}_i = \max \hat{\mu}_j \hat{\mu}_i$ and as above, the efficiency indice is measured as: $eff_i = \exp(\hat{u}_i)$. However, when the assumption of independence between the inefficiency parameter and input levels is being verified, a random effect model is generally preferable (Green, 1993). In such cases, firm-effects are treated as random variables and estimated using the variance components approach or generalized least square (GLS) approach. If we define residuals as: $\hat{\mu}_i = \frac{1}{T}\sum_t \hat{\mu}_{it}$.

6 Table A2 presents only the estimated coefficients of the random effects (GLS) because results show that we could not reject the hypothesis of non-correlation between the inefficiency term and inputs using a Hausman test in nine sectors. In sectors where the hypothesis was rejected, the differences between LSDV and GLS estimates are not important.

Table 1: Efficiency Levels by Initial Export Status: Panel (Random-effects)

	Food		Wood		Textile		Metal		All	
	Mean	N	Mean	N	Mean	N	Mean	N	Mean	N
Cameroon										
Initial non-exporters	3.0	13	3.7	7	5.8	4	1.8	10	3.1	34
Initial Exporters	6.0	5	5.9	4	10.0	1	3.9	5	5.5	15
All	3.8	18	4.5	11	6.7	5	2.5	15	3.9	49
Ghana										
Initial non-exporters	1.7	24	2.7	16	3.4	23	2.2	20	2.5	83
Initial Exporters	--	0	6.4	5	--	0	1.3	2	4.9	7
All	1.7	24	3.6	21	3.4	23	2.2	22	2.7	90
Kenya										
Initial non-exporters	1.1	8	2.6	16	2.2	12	0.8	13	1.8	49
Initial Exporters	4.4	3	6.0	6	1.1	5	1.9	7	3.2	21
All	2.0	11	3.5	22	1.8	17	1.2	20	2.2	70
Zimbabwe										
Initial non-exporters	1.8	14	5.5	10	3.5	15	3.0	5	3.4	44
Initial Exporters	4.5	11	5.4	5	3.2	21	4.3	13	4.0	50
All	3.0	25	5.5	15	3.3	36	4.0	18	3.7	94

Note: Efficiency is scaled such that maximum score is 10 and minimum is 0.

Table 2: Efficiency Levels by Initial Export Status (Time Variant Productivity model)

Cameroon		1993	1994	1995
	N	Mean	Mean	Mean
Initial non-exporters	34	3.5	2.7	2.4
Initial Exporters	15	4.2	5.1	5.4
All	49	3.7	3.4	3.3
Ghana		1991	1992	1993
	N	Mean	Mean	Mean
Initial non-exporters	83	2.4	2.4	2.1
Initial Exporters	7	3.2	4.2	4.7
All	90	2.5	2.5	2.3
Kenya		1992	1993	1994
	N	Mean	Mean	Mean
Initial non-exporters	49	1.8	0.7	2.0
Initial Exporters	21	2.4	2.0	3.2
All	70	2.0	1.1	2.4
Zimbabwe		1992	1993	1994
	N	Mean	Mean	Mean
Initial non-exporters	44	3.3	3.3	3.5
Initial Exporters	50	2.8	4.1	3.8
All	94	3.1	3.7	3.6

Note: Efficiency is scaled such that maximum score is 10 and minimum is 0.

In order to derive a firm-level efficiency index for each year of the sample period, we estimated equation (1) with time-variant efficiency parameters for each country. Following Cornwell, Schmidt, and Sickles (1990) we introduce a parametric function of time into the production function to replace the firm-specific technical efficiency as follow: $u_{it} = \theta_{i1} + \theta_{i2} t + \theta_{i3} t^2$. Results are presented in Table 2.

As commonly observed, exporters exhibit higher average efficiency levels than non-exporters during the period. However, this may simply reflect a selection effect, with the most efficient producers being most likely to export (Roberts and Tybout, 1997a). In the next section, we more formally test if the greater average efficiency of exporting firms can be associated with exports experience.

III. The relationship between exports and technical efficiencies

We now use the estimates of technical efficiency derived above to study the relationship between exporting and efficiency level and growth.[7] We first follow Kraay (1997) in taking the level of efficiency as the dependent variable, progressively adding both the history of exporting and the prior level of efficiency as explanatory variables.

Efficiency level

The most basic specification is the following equation:

$$(2) \qquad TE_{it} = \beta_1 TE_{i,t=1} + \beta_2 EXP_{i,t=1} + \beta_3 X_{it} + e_{it}$$

where TE_{it} is firm-level technical efficiency of firm i at time t {t=1,2,3}, $EXP_{i,t=1}$ is a dummy for exporters at time t=1 and X is a vector of exogenous variables that include firm's characteristics and competitive conditions (See Table A3 in the Appendix for variable description). In regression (a) we examine the relationship between time-invariant productivity level and initial export history. This specification is evidently prone to the problem that previous high efficiency will contribute both to current efficiency and to exporting. In order to control for self-selection of the efficient into exporting, we therefore include the efficiency for the first period in regression (b) using the time-variant efficiency index in time 2 and 3. Under a strong assumption, if the initial exporter dummy remains significant, then this can be interpreted as demonstrating a causal relationship from exporting onto efficiency. Specifically, it must be assumed that there is no serial dependence in e_{it}, (i.e. $E(e_{it}.e_{is}) = 0$ for all s, t), and that although firm performance and exports are jointly determined, exports are predetermined with respect to e_{it}.

The results of estimates of the efficiency level index in terms of firm-level characteristics are presented in Table 3. In both time-invariant (regressions a) and time-variant productivity models (regression b), we observe that initial exporters tend to exhibit significantly higher levels of efficiency than other firms during the period. These results are consistent with those of Roberts and Tybout (1997a), who found that exporting firms were more efficient than non-exporters.

[7] As noted by Kumbakar (1991) and Coelli and Battese (1996), one step estimation might lead to more consistent estimates. In such a case, a function of inefficiency coefficients is specified and estimated simultaneously to the frontier model. However, the firm-level inefficiency specification remains arbitrary. Furthermore, a test between the one step and two step estimation procedures is not possible given that the two specifications are not nested (Coelli, 1992).

Table 3: Determinants of Technical Efficiency Level

	(a) Random effect efficiency level OLS	**(b) Time variant efficiency level GLS**	**(c) Time variant efficiency level OLS**
Constant	1.971**	0.707**	0.694**
	(5.19)	(2.13)	(2.21)
Initial exporter	1.480**	1.339**	
	(3.10)	(4.35)	
Initial efficiency		0.389**	0.373**
		(8.97)	(5.43)
Continuous exporter			1.268**
			(2.71)
Entrant			1.347**
			(2.24)
Cameroon	0.933**	0.317	0.256
	(2.12)	(0.90)	(0.58)
Kenya	-0.969**	-0.836**	-0.161
	(2.43)	(2.66)	(0.41)
Zimbabwe	0.394	0.508	0.768*
	(0.94)	(1.61)	(1.80)
Micro	-0.096	0.395	0.269
	(0.24)	(1.06)	(0.49)
Medium	0.383	0.153	0.047
	(1.02)	(0.56)	(0.13)
Large	-0.096	-0.145	-0.347
	(0.17)	(0.41)	(0.68)
Wood	1.722**	0.735**	1.045**
	(4.17)	(2.26)	(2.56)
Textiles	0.688*	0.896**	0.668*
	(1.71)	(2.88)	(1.91)
Metals	-0.237	0.580*	0.728*
	(0.63)	(1.79)	(1.95)
Observations	303	606	303
R-squared	0.20	0.30	0.25
Prob > F [(a)]	0.00		0.00
Prob > χ^{2} [(a)]		0.00	

Note: t-statistics, based on robust standard errors in models (a) and (c), in parenthesis. * Indicate statistical significance at the 10% level **Indicate statistical significance at the 5% level.
[(a)] Probability that H_0: "All coefficients except constant is zero", is true.

In the next step, the variable EXP, which denoted whether the firm was exporting in the first period, is replaced by a richer depiction of export history which distinguishes between continuous exporters and new entrants. Following Kraay (1997), we estimate the following equation :

$$(3) \qquad TE_{it} = \alpha_1 TE_{i,t-1} + \alpha_2 DC_{i,t-1} + \alpha_3 DE_{i,t-1} + \beta X_{i,t} + e_{it}$$

where continuous exporters (DC) are defined as those firms which exported in both periods 1 and 2, and new exporters (DE) are firms which did not export in round 1 but did export in round 2. Non-exporters are firms which did not export in round 2. Thus, prior history of exporting is used to explain subsequent changes in efficiency. Note that whether the firm exported in round 3 is not used to classify firms since to do so would re-introduce self-selection effects: firms with the largest gains in efficiency between rounds 2 and 3 will be better able to export during round 3.

As shown in Table 3 regression (c), the coefficients of the dummies for continuous exporters and for new exporters are positive and significant. Thus, controlling for other determinants of changes in efficiency, exporting in one period raises efficiency in the next period. The effects are quite substantial: one additional year of exporting raises the efficiency of continuous exporters by 13%. Further, the coefficient on new exporters is larger than that for continuous exporters: the first year of exporting raises efficiency by 14%. This finding is consistent with the hypothesis that firms catch up as a result of encountering learning opportunities and competition, closing the gap with best practice at a diminishing rate. However, such an interpretation of the results rests on the same strong assumption.

Efficiency Growth

We now follow Bernard and Jensen (1999) in reformulating the analysis with the growth in efficiency as the dependent variable. We follow our previous structure of first introducing exporting only as a dummy describing behavior in period 1, and then replacing this with a richer description of exporting history. We start from the following equation:

$$(4) \qquad \Delta TE_{it} = \delta EXP_{i,t-1} + \beta X_{i,t} + e_{it}$$

where ΔTE_{it} denotes technical efficiency growth of firm i. Tables 4 and 5 examine the relationship between a firm initial export status and efficiency growth during the entire sample period (year 1 to 3) for different specifications using various control variables. All regressions are run using Huber-White corrections for heteroskedasticity.

We observe in Table 4 that firms' export status during the initial year is significantly correlated with productivity growth during the entire sample period, for all specifications.

In Table 5, we distinguish the performance of continuous exporters and new entrants in the exporting market, from non-exporters and quitters during the first two years of the survey. We observe that new entrants show a significant higher efficiency growth rates (12%) compared to non-exporters and quitters for all specifications during the entire period under consideration. Continuous exporters also show higher efficiency growth than non-exporters and quitters (10%).

Table 4: Technical Efficiency Growth and Initial Exports

	Model (a)	Model (b)	Model (c)
Constant	-0.223	-0.814**	-0.932**
	(1.19)	(2.67)	(2.33)
Initial Exporter	1.214**	1.000**	1.191**
	(3.17)	(2.20)	(2.26)
Kenya		0.288	0.256
		(0.62)	(0.53)
Zimbabwe		0.354	0.382
		(0.71)	(0.74)
Cameroon		-0.433	-0.454
		(0.87)	(0.92)
Wood		0.290	0.267
		(0.66)	(0.60)
Textile		0.478	0.449
		(1.21)	(1.14)
Metal		1.442**	1.321**
		(3.20)	(2.85)
Small			0.491
			(0.72)
Medium			0.330
			(0.75)
Large			-0.170
			(0.30)
Observations	303	303	303
R^2	0.04	0.08	0.08
Prob > F [(a)]	0.00	0.00	0.00

Note: Robust t-statistics in parenthesis. * Indicate statistical significance at the 10% level **Indicate statistical significance at the 5% level.
[(a)] Probability that H_0: "All coefficients except constant is zero", is true.

Table 5 : Technical Efficiency Growth and Categories of Exporters

	Model (a)	Model (b)	Model (c)
Constant	-0.191	-0.855**	-0.990**
	(0.98)	(2.76)	(2.48)
Continuous Exporter	1.088**	0.873*	0.964*
	(2.68)	(1.93)	(1.82)
Entrant	1.082*	1.164*	1.152*
	(1.67)	(1.90)	(1.87)
Kenya		0.232	0.197
		(0.50)	(0.41)
Zimbabwe		0.418	0.424
		(0.89)	(0.85)
Cameroon		-0.515	-0.534
		(1.01)	(1.06)
Wood		0.432	0.423
		(0.95)	(0.93)
Textile		0.539	0.527
		(1.35)	(1.32)
Metal		1.518**	1.438**
		(3.37)	(3.12)
Small			0.446
			(0.65)
Medium			0.320
			(0.73)
Large			-0.010
			(0.02)
Observations	303	303	303
R^2	0.03	0.08	0.08
Prob > F [(a)]	0.01	0.00	0.00

Note: Robust t-statistics in parenthesis. * Indicate statistical significance at the 10% level **Indicate statistical significance at the 5% level.

[(a)] Probability that H_0: "All coefficients except constant is zero", is true.

Dynamic Panel Estimation with Correlated Non-parametric Random Effects

A potentially serious problem with the above approaches is that exports and efficiency may be correlated for reasons other than causality running from exports to efficiency. In particular, there is reason to anticipate that there exists unobserved heterogeneity, say regarding firm management, affecting both efficiency and the propensity to export. Failure to control for such mechanisms will yield a spurious positive coefficient on export participation in single equation approaches such as those employed above. In order to address this problem and more formally test whether past exports influence the current efficiency level, we follow an alternative approach consistent with that of Clerides et al (1998). As these authors, we estimate the efficiency equation jointly with an export-participation equation. We estimate a dynamic system with the following structure:

(5) $$TE_{it} = \omega_1 TE_{i,t-1} + \omega_2 EXP_{i,t-1} + \omega_3 X_{i,t} + \mu_{i1} + e_{it1}$$

(6) $$EXP_{it}^{*} = \omega_4 TE_{i,t-1} + \omega_5 EXP_{i,t-1} + \omega_6 W_{it} + \mu_{i2} + e_{it2}, \qquad t = 2, 3,$$

where EXP^* is the latent export variable, W is a set of strictly exogenous variables explaining exports, μ_{i1} and μ_{i2} are unobserved firm specific time invariant effects affecting efficiency and exports, respectively, e_{it1} is normally distributed white noise with mean zero and variance σ^2, and e_{it2} is normally distributed white noise, with mean zero and variance normalized to 1.We observe only the binary outcome of whether or not the firm exports, which, based on (6), follows the following dynamic discrete process:

(7) $$EXP_{it} = \begin{cases} 1 & \text{if } \omega_4 TE_{i,t-1} + \omega_5 EXP_{i,t-1} + \omega_6 W_{it} + \mu_{i2} + e_{it2} \geq 0 \\ 0 & \text{otherwise} \end{cases}$$

Given the normality assumption about e_{it2}, this yields the probit model.

We are mainly interested in estimating the coefficients on the lagged dependent variables, as these will shed light on i) if there is support for self-selection-into-exporting, i.e. that efficient firms become exporters (in which case ω_4 would be positive); ii) if there is support for learning-by-exporting, i.e. that firms improve efficiency as a result of exporting (in which case ω_2 would be positive); iii) if there are considerable fixed costs associated with exporting, so that firms tend to continue exporting once they have entered the international market (in which case ω_5 would be positive; see Roberts and Tybout, 1997b). To obtain consistent estimates of these coefficients requires that we control for heterogeneity between firms, or we would expect ω_1 , ω_2 , ω_3 and ω_4 to be upward biased (see e.g. Heckman, 1981, for the distinction between true and spurious state dependence). Although the set of regressors used in previous sections proved useful in controlling for observed heterogeneity, it is likely that unobserved factors, such as managerial ability, are important too (for instance, good management enhances both efficiency and propensity to export). Furthermore, it seems plausible that the unobserved factors affecting technical efficiency are correlated with the unobserved factors affecting exports.

To deal with these issues of unobserved heterogeneity, we specify the μ:s as $\mu_{il} = \gamma_l Z$, l=1, 2, where Z is a firm specific time invariant random effect and the γ:s are factor loadings. To integrate the random effects out of the likelihood, contrary to Clerides et al who assume the random effects to be bivariate normal, we follow Heckman and Singer (1984) and adopt a non-parametric strategy for characterising the distribution of the random effects. Specifically, we assume that the (unknown) distribution of Z, $g(Z)$, is approximated by a discrete multinomial distribution with M points of support:

$$Z = z_m \cdot \theta \quad \textit{with probability } P_m, \qquad m = 1,2,\ldots,M; \ \sum_{m=1}^{M} P_m = 1,$$

where the z:s, the P:s, and θ are parameters to be estimated, along with the factor loadings and the other parameters of the model. Hence, the estimated support points determine where the observations are positioned, and the P:s indicate the proportion of the observations found at each particular point. Usually, the number of support points is small. Indeed, for $M = 1$ unobserved heterogeneity is absent and the exports and efficiency equations are hence independent. In this special case, standard maximum likelihood (ML) procedures may be used to estimate the parameters of interest.

The non-parametric discrete form is flexible and several restrictions inherent in the bivariate normal approach (e.g. symmetric distribution of heterogeneity) are avoided. Moreover, Heckman and Singer demonstrated that the discrete form works well even if the true distribution is continuous (see also Mroz, 1999). In estimating the model, one important issue refers to the number of support points, M. In fact, there are no well-established criteria for determining M in models like these (see e.g. Heckman and Walker, 1990), so we will follow standard practice and increase M until there are only marginal improvements in the log likelihood value.

In forming the likelihood we have to recognize the presence of lagged dependent variables among the explanatory variables. This creates an initial conditions problem in that TE_{i1} and EXP_{i1} are going to be correlated with the firm specific effect if these efficiency levels and export decisions were determined by the same model as that governing efficiency and exports from t=2 and onwards.[8] Neglecting the initial conditions problem would lead to inconsistent parameter estimates unless T tends to infinity. We approach this problem by specifying models for the initial conditions TE_{i1} and EXP_{i1}, allowing them to be functions of the random effects which we specify as $\mu_{il} = \gamma_l Z$, l=3, 4, respectively. The parameters of the initial conditions models are estimated jointly with the other parameters (see Heckman, 1981; Blau, 1994; Blau and Gilleskie, 1997). The full likelihood function is shown in the appendix.

Table 6 shows estimation results for the main efficiency and exports equations (Table A4 in the Appendix reports the estimates for the initial conditions).[9] As a benchmark, the first panel shows results for the case when there is no unobserved heterogeneity (i.e. equivalent to $M = 1$). Here, as expected, all four coefficients on the lagged dependent variables are positive and significant. In the second panel we report the NPML results allowing for unobserved heterogeneity, where $M = 4$.[10] Compared to the benchmark results in the first panel, the coefficient on lagged efficiency in the efficiency regression decreases somewhat (from 0.45 to 0.37) but remains significant, whereas the other coefficients on the lagged dependent variables are subject to minor changes only. Note however that lagged efficiency in the export probit now is less significant than under no unobserved heterogeneity. Still, consistent with

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8 A simple example may illustrate this: Consider a process where y_t depends on y_{t-1} and a random effect z, and define the per-period likelihood contribution as $f(y_t \mid y_{t-1}, z)$. Since z is unobserved we need to integrate over its distribution in order to formulate the likelihood solely in terms of observable variables. If y_0 for some reason is independent of z, the likelihood unconditional of z is simply $\int \Pi_{t=1} f(y_t \mid y_{t-1}, z)\, dG(z)$. In this case there is no difference compared to the static counterpart of the model. However, if y_0 is dependent of z , say because the process begun before the time of the first observation of the sample, the likelihood is equal to $\int \Pi_{t=1} f(y_t \mid y_{t-1}, z)\, h(y_0 \mid z)\, dG(z)$, where $h(y_0 \mid z)$ denotes the marginal density of y_0 given z. Dealing with $h(y_0 \mid z)$ is the initial conditions problem (see e.g. Hsiao, 1986, pp. 169-172).

9 Estimation was done in SAS, using the IML Newton-Raphson Ridge Optimization Method (NLPNRR). The likelihood function is not globally concave, so we have used several different start value sets to guard against convergence at local maxima.

10 There are no variables in the models for initial conditions that are not included in the main equation. The model is nevertheless identified because of the nonlinearity of the discrete factor specification (Blau and Gilleskie, 1997).

Bernard and Jensen (1999) and Clerides et al (1998) we find evidence of self-selection by the relatively more efficient firms into-exporting, as lagged efficiency positively affects the probability of exporting. However, contrary to these authors, we observe that *lagged export participation significantly increases efficiency, even after controlling for unobserved heterogeneity*. Thus, our results provide support for the learning-by-exporting hypothesis. Furthermore, there is evidence that there are large fixed costs associated with exporting: lagged export participation has a significant and large positive effect on the probability of exporting.

As for the importance of unobserved heterogeneity, it is clear from Table 6 that there is a considerable improvement in the log likelihood value when going from the benchmark model to the heterogeneity model. Table A5 in the Appendix summarizes the unobserved heterogeneity results. We see that 63% of the discrete distribution occurs at the lowest support point (m=1) and 19% at the second lowest (m=3). For the efficiency model the lowest support point is –0.53 and the highest is 0.53; since efficiency is multiplied by 10 this means that efficiency varies roughly 10 percentage points due to unobserved heterogeneity. For exports, however, unobserved heterogeneity seems to play only a minor role, ranging between –0.023 and 0.023.

IV. Conclusion

In this paper, we have examined two not-incompatible explanations for the positive association between export-participation status and productivity: self-selection of the relatively more efficient plants into exporting, and learning by exporting, using panel data on manufacturing firms in four small African countries. Previous studies have considered either the USA or medium-sized, open developing economies. For the USA exporting had no effect on efficiency. This is not surprising given that the US is the largest, most competitive and most technologically advanced economy. In the medium sized developing economies the results were ambiguous. The four African economies which constituted the sample for the present study have characteristics at the opposite end of the scale to the USA : they are small, have a history of high trade restrictions and low levels of competition, and are technologically backward. *A priori*, African manufacturers are therefore more likely than those in other regions to reap efficiency gains from exporting. This was borne out by our results. In contrast to previous results, we have found that exporting has a large and significant effect on efficiency. Even for firms which have a previous history of exporting, an additional year of exporting raises efficiency in the next period controlling for other factors by 10%. The efficiency gain for a new entrant to exporting is even larger. To formally test whether the association between exporting and efficiency reflects more than self-selection, we simultaneously estimated an efficiency function and a dynamic discrete choice equation of export market participation accounting for correlated error terms, using non-parametric maximum likelihood. Our estimates yield results similar to those reported by Bernard and Jensen (1999) and Clerides et al (1998) regarding the presence of sunk costs into exporting and of the self-selection of the relatively most efficient firms into the export market. Furthermore, contrary to previous results, we find that our data is consistent with a causality pattern also flowing from exporting experience to improvements in performance, providing support for the learning-by-exporting hypothesis . The distinctive nature of these results for Africa when compared for those with other regions suggests that whether or not there are efficiency gains from exporting depends upon the market environment in which the firm is located : smaller markets and technological backwardness make the export experience more advantageous. If this is correct then, contrary to the suggestions of some commentators, Africa has more to gain than other regions from orientating its manufacturing sector towards exporting.

Table 6. Technical Efficiency and Exports

	(a) ML Estimates: No unobserved heterogeneity			(b) NPML Estimates: Correlated Discrete Random Effects		
	A. Linear Regression: Efficiency					
	Coef	std	z	Coef	std	z
Constant	0.72	0.27	2.70	1.20	0.33	3.62
Efficiency t-1	0.45	0.04	12.88	0.37	0.05	7.21
Exports t-1	1.14	0.24	4.68	1.12	0.24	4.63
Cameroon	0.28	0.28	0.98	0.26	0.28	0.93
Kenya	-0.57	0.26	-2.21	-0.63	0.26	-2.47
Zimbabwe	0.46	0.25	1.82	0.47	0.25	1.86
Wood	0.73	0.26	2.81	0.72	0.26	2.79
Textile	0.66	0.25	2.65	0.72	0.25	2.87
Metal	0.40	0.26	1.57	0.46	0.26	1.78
Small	0.27	0.33	0.81	0.33	0.33	1.00
Medium	0.08	0.24	0.35	0.19	0.24	0.77
Large	-0.21	0.29	-0.73	-0.10	0.30	-0.33
γ_1				1.00	--	--
σ^2	4.72	0.27	17.41	4.67	0.27	17.37
	B. Probit: Export Participation					
	Coef	std	z	Coef	std	z
Constant	-2.41	0.30	-8.06	-2.40	0.33	-7.16
Efficiency t-1	0.08	0.03	2.69	0.08	0.04	1.90
Exports t-1	2.20	0.18	12.39	2.19	0.18	12.36
Public	0.00	0.35	0.01	0.00	0.35	0.01
Foreign	0.12	0.20	0.60	0.11	0.20	0.57
Cameroon	0.48	0.25	1.95	0.48	0.25	1.95
Kenya	0.45	0.24	1.86	0.45	0.25	1.84
Zimbabwe	0.30	0.23	1.31	0.30	0.23	1.31
Wood	-0.18	0.25	-0.71	-0.18	0.25	-0.72
Textile	0.32	0.22	1.45	0.33	0.22	1.46
Metal	0.29	0.23	1.29	0.29	0.23	1.29
Small	-0.36	0.41	-0.88	-0.35	0.41	-0.87
Medium	0.41	0.23	1.75	0.41	0.24	1.73
Large	0.80	0.26	3.04	0.81	0.27	2.98
γ_2				0.04	0.35	0.12
θ				1.05	0.44	2.39
Log L		-2319.78			-2195.62	
N, T, N*T			303, 2, 606			

Note: For Model [2] heterogeneity have four points of support. For heterogeneity parameters see Table 2. For parameter estimates for initial conditions, see Appendix A2.

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Appendix 1

Table A1: Summary Statistics of Variables by country

Cameroon

Variable Label	N	Mean	Std Dev	Minimum	Maximum
Value Added	189	1498339.53	3486086.11	232.37	25900423.73
Capital	189	2519891.28	6097553.47	540.35	52966101.69
Employment	189	89.57	200.84	2.00	1520.00
Exports/output	188	0.12	0.26	0	1
Foreign	189	0.37	0.48	0	1
Micro firms	189	0.11	0.31	0	1

Ghana

Variable Label	N	Mean	Std Dev	Minimum	Maximum
Value Added	279	159100.34	568571.81	61.62	5002358.73
Capital	279	644031.37	2875168.89	77.03	34317089.91
Employment	279	40.83	76.67	1.00	505.00
Exports/output	274	0.04	0.17	0	1
Foreign	279	0.16	0.37	0	1
Micro firms	279	0.14	0.35	0	1

Kenya

Variable Label	N	Mean	Std Dev	Minimum	Maximum
Value Added	210	604731.57	1523988.29	20.17	10346057.80
Capital	210	1282617.25	2381730.52	178.41	17380509.00
Employment	210	0.89	1.59	1	18.00
Exports/output	210	0.14	0.31	0	1
Foreign	210	0.17	0.38	0	1
Micro firms	210	0.15	0.36	0	1

Zimbabwe

Variable Label	N	Mean	Std Dev	Minimum	Maximum
Value Added	282	2645496.71	8274830.47	98.08	77514711.65
Capital	282	5030507.54	18921634.58	1.35	255001962.00
Employment	282	285.46	405.24	3.00	2144.00
Exports/output	279	0.11	0.20	0	1
Foreign	282	0.26	0.44	0	1
Micro firms	282	0.05	0.21	0	1

Note: Value Added and capital in PPP. Value of Export/output, Foreign ownership and micro firms are fractions.

Table A2: Estimated Parameters of the Frontier Production Function: Panel (Random-effects)

Country	Sector	n	intercept	labour	capital	R^2
Cameroon	Food	54	6.31 (1.15)	0.72 (.19)	0.31 (0.12)	0.71
	Wood	33	0.92 (0.93)	0.93 (0.21)	0.64 (0.10)	0.77
	Textiles	15	1.25 (1.18)	1.02 (0.26)	0.58 (0.12)	0.87
	Metals	45	4.18 (1.57)	1.14 (0.22)	0.35 (0.15)	0.77
Ghana	Food	72	8.42 (0.67)	0.76 (0.17)	0.10 (0.07)	0.38
	Wood	63	7.02 (0.68)	0.54 (0.19)	0.22 (0.07)	0.41
	Textiles	72	6.69 (0.53)	0.48 (0.16)	0.19 (0.06)	0.30
	Metals	66	6.37 (0.64)	1.09 (0.22)	0.15 (0.09)	0.59
Kenya	Food	33	3.62 (2.12)	0.90 (0.27)	0.48 (0.17)	0.57
	Wood	66	7.49 (1.11)	1.09 (0.18)	0.07 (0.11)	0.52
	Textiles	51	7.99 (1.22)	0.91 (0.28)	0.08 (0.15)	0.51
	Metals	60	4.09 (1.12)	0.58 (0.29)	0.50 (0.15)	0.65
Zimbabwe	Food	75	5.61 (1.16)	0.95 (0.20)	0.28 (0.12)	0.65
	Wood	45	6.58 (0.71)	1.04 (0.16)	0.15 (0.09)	0.89
	Textiles	108	4.85 (0.36)	0.96 (0.10)	0.29 (0.05)	0.87
	Metals	54	5.81 (0.90)	0.91 (0.22)	0.28 (0.11)	0.78

(Standard-errors in parenthesis)

Table A3: Variables description

Variable	Definition
INTERCEP	Intercept
INITIAL EXPORTER	Intial exporter: 1 if exports in period 1; 0 otherwise
CONTINUOUS t-1	Dummy continuous exporter in wave 2 (1 1 1, 1 1 0): 1 if firm exported in both periods 1 and 2, 0 otherwise
ENTRANTS t-1	Dummy new entrant into exporting in wave 2 (0 1 1, 0 1 0): 1 if firm didn't export in round 1 but did export in round 2, 0 otherwise
CAMEROON	Dummy Cameroun: 1 if country=Cameroon, 0 otherwise
ZIMBABWE	Dummy Zimbabwe: 1 if country =Zimbabwe, 0 otherwise
KENYA	Dummy Kenya: 1 if country =Kenya, 0 otherwise
MICRO	Dummy micro 1 if 1<employment<4, 0 otherwise
MEDIUM	Dummy medium: 1 if 30<employment<99, 0 otherwise
LARGE	Dummy large: 1 if employment =100 or more, 0 otherwise
WOOD	Dummy wood: 1 if sector = wood, 0 otherwise
TEXTILES	Dummy textiles: 1 if sector =textiles, 0 otherwise
METALS	Dummy machines:1 if sector = machines, 0 otherwise
FOREIGN OWNED	Dummy foreign ownership: 1 if ownership=foreign , 0 otherwise
PUBLIC OWNED	Dummy public ownership: 1 if ownership=public, 0 otherwise
INITIAL EFFICIENCY	Efficiency level in period 1
EFFICIENCY t-1	Efficiency level in period t-1

Appendix 2
The likelihood function for regressions reported in Table 6

Conditional on X, W, μ_{i1} and μ_{i2}, we have the following two components of firm *i*'s contribution to the likelihood in periods t=1,2,…,T:

i) Efficiency: $$L_i^{TE} = \prod_{t=1}^{T} \sigma^{-1}\phi\{(TE_{it} - X_{it}'\beta - c_1 EXP_{i,t-1} - c_2 TE_{i,t-1} - \mu_{i1})/\sigma\},$$

ii) Exports: $$L_i^{EXP} = \prod_{t=1}^{T} \Phi\{(W'_{it}\delta + g_1 EXP_{t-1} + g_2 TE_{i,t-1} + \mu_{i2})(2EXP_{it} - 1)\},$$

where $\phi(.)$ and $\Phi(.)$ are the density and the c.d.f. of the normal distribution, respectively. To address the initial conditions problem we add to the system two equations modelling efficiency and exports at t=0:

iii) Efficiency: $$L_i^{TE_0} = \sigma_0^{-1}\phi\{(TE_{i0} - IX_{i0}'\beta_0 - \mu_{i3})/\sigma_0\},$$

iv) Exports: $$L_i^{EXP_0} = \Phi\{(IW'_{i0}\delta_0 + \mu_{i4})(2EXP_{i0} - 1)\},$$

where *IX* and *IW* are vectors of explanatory variables. Hence, firm *i*'s total contribution to the likelihood is equal to the product of these four components. To make the likelihood unconditional on the unobserved firm specific effects, we need to integrate over the associated distribution. Recall that we specify the μ:s as

$$\mu_{il} = \gamma_l Z, \; l=1,2,3,4,$$

where *Z* follows a discrete distribution:

$$Z = z_m \cdot \theta \quad \textit{with probability } P_m, \quad m = 1,2,\ldots,M; \; \sum_{m=1}^{M} P_m = 1.$$

Hence, integrating out the random effects means summing over the distribution of *Z*:

$$L_i = \sum_{m=1}^{M} P_m \, L_i^{TE}(.|\gamma_1\theta z_m) \cdot L_i^{EXP}(.|\gamma_2\theta z_m) \cdot L_i^{TE_0}(.|\gamma_3\theta z_m) \cdot L_i^{EXP_0}(.|\gamma_4\theta z_m).$$

It is necessary to make a number of identifying restrictions (see Blau, 1994). We make the following: $\gamma_l=1$; $z_1=-0.5$; $z_M=0.5$; $z_m = (1 + \exp(-a_m))^{-1} - 0.5$. The restrictions on z means that only M-1 support points will be estimated. This is because we include intercepts in the four models. Finally, the sample likelihood is the product of all individual likelihood contributions:

$$L = \prod_{i=1}^{N} L_i .$$

Appendix 3
Auxiliary results from regressions reported in Table 6

Table A4: Initial Conditions for Technical Efficiency and Exports

	[1] No unobserved heterogeneity			[2] Correlated Discrete Random Effects		
	A. Linear Regression: Initial Efficiency					
	coef	std	z	coef	std	z
Constant	2.40	0.45	5.38	4.83	0.21	22.97
Cameroon	1.36	0.46	2.95	0.40	0.22	1.81
Kenya	-0.51	0.42	-1.22	-0.35	0.17	-2.03
Zimbabwe	0.59	0.41	1.44	0.18	0.18	1.00
Wood	0.99	0.43	2.29	0.24	0.17	1.41
Textile	0.27	0.41	0.64	0.17	0.18	0.91
Metal	-1.09	0.42	-2.61	-0.37	0.16	-2.26
Small	0.26	0.51	0.51	0.37	0.23	1.57
Medium	-0.01	0.40	-0.03	0.48	0.19	2.50
Large	0.01	0.44	0.02	0.48	0.23	2.13
γ_3				7.64	3.19	2.39
s^2	6.46	0.52	12.31	0.51	0.06	8.06
	B. Probit: Initial Export Participation					
	coef	std	z	coef	std	z
Constant	-2.92	0.42	-7.00	-2.85	0.43	-6.69
Public	-0.09	0.42	-0.22	-0.03	0.42	-0.07
Foreign	0.26	0.23	1.15	0.15	0.24	0.62
Cameroon	0.83	0.33	2.50	0.82	0.34	2.43
Kenya	0.63	0.31	2.04	0.68	0.31	2.15
Zimbabwe	1.08	0.30	3.60	1.09	0.30	3.61
Wood	0.59	0.29	2.05	0.55	0.29	1.88
Textile	0.46	0.28	1.63	0.46	0.28	1.63
Metal	0.88	0.28	3.21	0.98	0.29	3.41
Small	-0.28	0.55	-0.50	-0.26	0.55	-0.46
Medium	1.04	0.31	3.32	1.12	0.32	3.45
Large	2.14	0.34	6.35	2.24	0.35	6.39
γ_4				0.47	0.37	1.29

Table A5. Unobserved Heterogeneity Results

	a_m	P_m	Efficiency: $\mu_1 = z_m * \theta * \gamma_1$	Exports: $\mu_2 = z_m * \theta * \gamma_2$	Initial Eff.: $\mu_3 = z_m * \theta * \gamma_3$	Initial Exports: $\mu_4 = z_m * \theta * \gamma_4$
m=1	-∞	0.626	-0.527	-0.023	-4.028	-0.248
		(0.062)				
m=2	1.134	0.095	0.257	0.011	1.960	0.121
	(0.163)	(0.018)				
m=3	-0.248	0.187	-0.062	-0.003	-0.471	-0.029
	(0.123)	(0.042)				
m=4	+∞	0.092	0.527	0.023	4.028	0.248
		(0.022)				

Note: Standard errors in ( ). The transformed mass points are calculated as
$\mu_m = [\ (1 + \exp(-a_m)\ )^{-1} - 0.5\ ] * \theta * \gamma_m$.