Can agro-processing lead re-industrialisation in Sub-Saharan Africa? A two-stage approach to productivity analysis

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Abstract

This analysis sits against the backdrop of unsuccessful attempts to reindustrialise Africa. Zambia must diversify from copper dependency to agriculture and the agro-processing sectors, and the question is whether there is enough capacity to deliver jobs or growth. This paper studied the agro-processing sector, where mean technical efficiency was 42.5% and mean scale efficiency was 81.7%. Beverage firms fared better than food producers and, within food production, meat processing did best, while baking and milling firms did the worst. There are benefits to centralisation and being large scale, although one in five firms was too large. A reindustrialisation programme should focus on the promotion of modern technologies, capacity building and infrastructure development, as well as on improvements in the regulatory framework.

Key words: DEA; Tobit; agro-processing; reindustrialisation; Farrell efficiencies; Zambia

1. Introduction

The deindustrialisation of Africa and the poor performance of its manufacturing sector are widely lamented in the development literature (Page 2011; Rodrik 2013; McMillan & Headey 2014). This paper investigates Page's (2011) assertion that agro-processing could lead the reindustrialisation of Zambia. Although the data are more problematic than we would have liked, it is a new source and the study does contribute to the small set of productivity studies of African manufacturing (Lundvall & Battese 2000; Gebreeyesus 2008; Ngui-Muchai & Muniu 2012). For Zambia, the paper relates productivity studies in the public realm (Masiye 2007; Masiye *et al*. 2014) to private sector performance.

When Zambia gained independence in 1964, it had a copper economy. In the beginning, the country benefitted from manufacturing firms fleeing the unilateral declaration of independence in the then Rhodesia in 1965. With the *Mulungushi* and *Matero* reforms of 1968 and 1969, the Zambian government wanted to accelerate the transformation of ownership of assets by taking a bigger stake in the economy (Kaunga 1995). This happened rapidly. By 1972, parastatals accounted for 53% of the manufacturing sector's contribution to GDP and 42% of all manufacturing jobs (Fundanga & Mwaba 1997). The reforms were funded by a buoyant copper price, but this collapsed following the 1974 oil crisis. The share of mining in GDP fell from 33% in 1976 to just over 10% by 1978, and has never recovered. Initially, the government tried to keep the economy afloat by taking even greater stakes in manufacturing, now funded with foreign debt. By the early 1990s, unsustainable levels of borrowing led to hyperinflation and food riots, and eventually to a change in government. With the country's political transition to a multiparty democracy in 1991, the International Monetary Fund became heavily involved and insisted on deregulation. This was initially good for growth (Saasa 1996; Fundanga & Mwaba 1997), although the drastic reduction of tariffs, and widespread corruption, eventually caused extensive capital flight, which almost brought manufacturing to its knees (UNIDO 2013). Given Zambia's fertile soils and abundant water resources, agriculture is important for growth and, with abundant agricultural commodities, agro-processing is a logical candidate for reindustrialisation. As a first step towards answering this question, this paper examines the total factor productivity performance of food and beverage firms in Zambia. The benchmarking process will reveal what the typical agro-processor looks like, and how much room there is for scale and technical efficiency improvements.

Section 2 briefly explains the two-stage approach to productivity analysis. Section 3 summarises the results under the subheadings "general performance patterns" and "determinants of efficiency", and the paper ends with some recommendations for how to revive this part of the manufacturing sector.

2. Methods

The main objective of Zambia's Economic Census of 2010 was to put the country's balance-of-payments statistics on firmer ground (Central Statistical Office [CSO] 2012). Phase 1 of the census process listed all firms that do business in malls, markets and informally out of shipping containers or similar structures, as well as large-scale commercial firms. Phase 2 then collected data for the 2010 financial year from all large and medium-sized manufacturing firms, plus a 10% sample of small-scale firms. This dataset yielded a potential sample size of 174 observations for the agro-processing sector, the dominant part of manufacturing.

There are several quality problems with this data. Firstly, 59 agro-processing firms submitted returns that were deemed incomplete by the Statistical Office. Data cleaning revealed a further 24 incomplete or inconsistent responses that we fixed by imputation. This left a sample size of n = 115 useable observations – too few to fit Batesse and Coelli's (1995) inefficiency model. Secondly, we suspect that data collection might have been spatially uneven, since there was an undue level of concentration of firms in Lusaka Province. Short of further data collection, there is nothing that could be done to correct for this problem. Thirdly, manufacturing might have been rather loosely defined. For example, although the Zambian climate is unsuited to the production of wine grapes, the census reported the existence of a winery near Lusaka, which is more likely to be a wholesaler than a producer of wines. This kind of conflation of trade and manufacturing was present in the milling sector too, where some firm names clearly indicated a retail orientation rather than evidence of agro-processing. However, there are many cases in which local retailers are also involved in the processing of raw materials procured locally. We are just not able to say to what degree a particular firm's efficiency advantage derives from vertical integration and trade as opposed to efficient manufacturing. Given these data limitations, care should be taken not to over-extrapolate from this case study.

The dataset was issued with a dummy variable indicating three size categories based on turnover. The cut-offs for small and medium size status was ZMK 250 000 and ZMK 800 000 (in new currency after rebasing) respectively. There were 49 large, four medium and 52 small firms in the sample, which points to a high degree of duality. Since the size variable based on turnover was inconsistent with other important variables in the dataset, it was replaced with a dummy variable based on employment, which performed more reliably. Firms with ≥ 50 employees were defined as large and those with employment of ≥ 11 and ≤ 49 were classified as medium sized. The remainder were called small. We expected larger firms to be more scale efficient and perhaps less technically efficient due to the increasing marginal cost of supervision.

Zambia's ten provinces were aggregated into three regions so that a meaningful regional comparison could be made. The Central Region included Central Province, Lusaka Province, Copperbelt and the Eastern Province. The Northern Region consisted of Luapula Province, Muchinga Province and Northern Province. The Western Region comprised the Southern, Western and North-Western Provinces. We expected firms in the Central region to be more technically efficient than firms located in the two more remote regions, since the cost of doing business would be lower in the capital than in the more remote regions. There was no reason to believe that scale efficiencies would vary spatially.

The Battese and Coelli (1995) approach, which fits an inefficiency model simultaneously with a stochastic frontier specification, is always preferable where sample size is sufficiently large to tolerate this complexity (e.g. Taymaz & Saatçhi 1997; Aedo *et al*. 2011; Lakner *et al*. 2013). The statistically inferior two-stage procedure, in which a data envelopment analysis (DEA) is followed by a Tobit estimation, is a better strategy for sample sizes as small as ours, but this semi-parametric approach is nonetheless well documented in the literature. Amongst others it has been employed to investigate small-scale manufacturing in Pakistan (Burki & Terrell, 1998), rice farming in Nepal (Dhungana *et al*. 2004), sugar production in Uttar Pradesh (Kumar & Arora, 2011), operational efficiency in global airlines (Scheraga 2004), as well as analysing the performance of Italian and Greek agro-processing firms (Bonfiglio 2006; Rezitis & Kalantzi 2015). In Leachman *et al*. (2005), DEA was even followed by OLS, although we now know that the typical distribution of efficiency scores violates the assumptions of an OLS model.

Our efficiency scores were produced with the DEAP 2.1 algorithm, which implements the Banker *et al*. (1984) refinement of the original constant returns to scale model proposed by Charnes *et al*. (1978). The output included sales and receipts. The inputs considered were the cost of labour, the running cost of capital (fuel plus electricity) and raw materials (Table 1). The census collected information on depreciation too, but after much experimentation we decided that we trusted the data on the running cost of capital more. A variable returns-to-scale frontier decomposed overall technical efficiency into pure technical and scale efficiency, each measured on a range of zero to one. Fully efficient firms lie on the frontier and serve as industry benchmarks.

Table 1: Variables defining efficiency in the Zambian agro-processing sector

Variable Name	Measurement	Sample	Mean	Std dev
Gross output (ZMW)	Sales + Receipts	115	18 136 845	17 579 106
Capital (ZMW)	Energy = Electricity + Fuel	115	416 264	2 704 353
Labour	Number of workers per firm	115	62	301
Materials (ZMW)	Cost of raw materials + changes in stock of raw materials	115	11 656 461	70 162 960

ZMW = Zambian Kwacha. It was rebased in 2010 by dropping three zeros (i.e. ZMW1 000 became ZMW1), when the average exchange rate when ZMW4.8 = US$1. Also, ZMW1 = ZAR0.742

The second-stage Tobit model explains technical efficiency with a capital-labour ratio, a proxy for firm size, the firm's scale efficiency score, its market share, dummy variables for labour quality and firm-level R&D. Preliminary analyses are reported in Appendix II. We fitted different models for large and small-scale firms, as different types of production technologies were hypothesised to be at work in the two scales. Higher capital-labour ratios were expected to improve technical efficiency (Bonfiglio 2006). The evidence for the effect of size on efficiency was more ambiguous. Lundvall and Batesse (2000) and Bhandari and Kay (2007) found that larger firms were more efficient in Kenyan manufacturing and in Indian textile firms respectively, but McPherson (1995) reported that in Southern Africa there were cases where smaller firms were more efficient than their larger counterparts. We expected that there would be a positive relationship between size and efficiency for large-scale firms, but that this relationship would not be significant for the SME portion of the agro-processing industry. Size was measured by the number of employees. Our third variable was the scale efficiency score obtained from DEA, and the assumption was that better capacity utilisation would improve efficiency (Ngui-Muchai & Muniu 2012). Since Leachman *et al.* (2005) showed that R&D commitment was positively correlated with efficiency, we too expected our R&D dummy to be positively correlated with technical efficiency. This variable was only included in the large-scale cohort, since none of the small-scale firms reported any in-house R&D expenditure.

We also experimented with market share calculated at the product level to see if Sekkat's (2009) finding for Jordan and Morocco, namely that competition impedes efficiency, generalises to Southern Africa. We found that, as in Egypt, there was no correlation between the two in Zambia, and therefore this variable was dropped from the final specification of the Tobit model. In the case of foreign involvement, the evidence was mixed again. Kravtsova (2008) found that the employment of expat workers was positively correlated with efficiency, but Scheraga (2004) reported the opposite. Our dummy variable for expat workers provided no traction and was therefore dropped as well. Many authors, including Burki and Terrell (1998) and Dhungana *et al.* (2004), have found that higher levels of workers' education improves productivity. Unfortunately, this dataset did not have the average level of education of workers in the sector, although we did have a dummy variable indicating the presence of in-house training, which was expected to be positively correlated with technical efficiency. It was not significant and therefore not included in the final specification.

3. Results

3.1 Broad patterns of efficiency

Zambia's agro-processing industry is hampered more by a lack of technical efficiency (42.5%) than by scale inefficiency (81.7%). The two components were found to be inversely correlated ($r = -0.218$, $p \leq 0.019$), which means that right-sized firms tended to be worse at converting inputs into outputs than firms that were not right-sized, while others that had good capacity utilisation were not very good at converting inputs into outputs. The mean levels of scale technical efficiency, however, suggest that technical competence was more of an issue than optimal capacity utilisation. This, in turn, means that access to skilled labour is probably more of an issue than access to capital. Only 4% of firms invest in R&D, and only 7% in staff training programmes. A total of 20 firms were found to be fully technically efficient, while eight firms were fully scale efficient. For the remainder, performance could be addressed by either improving utilisation or by better management.

Just seven firms were found to be both technically and scale efficient. Of these seven, only one firm, a small bakery, was situated in a remote region – the Western province. Clearly, the cost of doing business far away from the central hub creates problems for firms. However, the census data did not have sufficient information for us to conclude whether firms in remote areas struggled more with finding skilled workers and getting access to financial services, or simply cannot compete because they face higher transport costs. Within the Central Region, where the cost of doing business is lower, the best-practice frontier was described by two large and four medium-sized firms. The two large-scale firms in this group of six were both grain millers, which points to economies of scale in this sector. The four medium-sized frontier firms were more diverse and included a meat-packing plant, an animal feeds manufacturer, a firm involved in the production of "other" foods, and one in the pressing of vegetable and animal oils. Although scale might play a minor role in the case of these four firms, they must have other advantages too, for example a more competent than average management team or more productive than average labour force. Unfortunately, the dataset again lacked information on the specific histories and circumstances of these benchmark enterprises. Thirteen firms were found to be technically efficient but not scale efficient, while one firm was only scale efficient. This implies that 11% of the sampled firms employ best-technology practices but operate at inefficient scales. Four firms were found to be too large and thus operating under decreasing returns to scale, while the other nine were operating on a very small scale under strongly increasing returns to scale. Small-scale firms that were too small tended to be concentrated in the Central and Western Regions and to be specialised in grain milling, soft drinks and bottled water, and animal and vegetable oils.

Table 2: Firm efficiency by type of agro-processing

All firms (n = 115)			**Food (n = 101)**		**Beverages (n = 14)**	
	TE	SE	TE	SE	TE	SE
Mean	0.425	0.817	0.403	0.821	0.587	0.789
Minimum	0.009	0.030	0.009	0.03	0.052	0.259
Median	0.294	0.914	0.273	0.913	0.6535	0.9295
Maximum	1	1	1	1	1	0.998

Note: TE = technically efficient; SE = scale efficient

Disaggregating the agro-processing industry into food and beverage producers offers further insight (Table 2). The comparison was as follows: for beverages, the mean performance was 59% technical efficiency combined with 79% scale efficiency, which gives an overall score of 46%. On the food side, a much worse technical efficiency of 40%, combined with a slightly better scale efficiency of 82%, gives an overall efficiency score of 33%. The bottom half of the firms in the food sector were only 27% technically efficient, but 91% scale efficient. This implies that the emphasis for agro-industrialisation should be on adopting appropriate technologies in input utilisation, and not so much on trying to grow at the extensive margin. The relatively better performance in beverages, of 65% technical and 93% scale efficiency, suggests that food producers can learn from beverage manufacturers.

3.2 Correlates of firm efficiency

Table 3 begins to delve into possible reasons for the observed variation in firm-level efficiency amongst agro-processing firms in Zambia. The first ANOVA test compared efficiency between and within subsectors. Pure technical performance varied more marginally across than within each of the subsectors. Beverages and meat/fish processing were the technically most proficient sectors, while the baking and milling subsectors showed the most room for improvement in technical efficiency. The beverage sectors comprised 14 firms involved in large-scale beer brewing, wine making, small-scale soft drink bottling, large-scale juice manufacturing and whisky distilling. In contrast to the technically advanced manufacturing processes employed by beverage producers and meat packers, small-scale fish processing is a simple affair that involves just gutting and sun drying of locally caught fish. In the baking and milling sectors, baking operations tend to be similarly quite small-scaled and simple, often involving just one worker operating a hammer mill.

The remaining 28 firms that did not fit these three sectors included both large and small firms from a variety of food and agro-processing businesses, so it did not come as any surprise to see that, as a group, they had an intermediate level of technical efficiency. More data would allow the construction of more meaningful subsector groups, the analysis of which ought to provide better insight into competitive advantage. In an ANOVA test with test statistic $F = 1.67$ ($p \leq 0.161$), these results indicate that no single subsector of Zambian agro-processing has a clear technical efficiency advantage over any other subsector.

The ANOVA tests compared technical and scale efficiencies across the size of the workforce and produced significant results for both scale and technical efficiency. The first of these tests indicated that technical efficiency increased with firm size ($F = 7.45$, $p \leq 0.001$), which means that the potential benefits of employing large-scale modern technologies outweigh the additional supervision costs implicit in having a larger labour force. This finding confirms Jovanovic's (1982) selection theory, which argues that efficiency increases with firm size, and thereby also confirms earlier findings of this relationship in manufacturing in sub-Saharan Africa (McPherson 1995; Lundvall & Battese 2000). The only caveat is that the census data was dominated by small-scale milling firms (see Appendix I), whose operations are highly seasonal and could impact the overall technical efficiency of the small-scale firms. Thus, a more robust longitudinal dataset would help to quantify the effect of seasonality on firm efficiency and ascertain the validity of the finding. The second test points to some diseconomies of scale at both ends. The category that achieved the best capacity utilisation was medium-sized firms, whose mean scale efficiency was 97%. A substantial portion of large firms were too large, while the majority of the scale-inefficient small firms would benefit from increasing their scale of operation. Bakeries (91%) and meat processors (88%), which tend to be medium-sized or large, did better than the other subsectors.

Table 3: Variation in efficiency in Zambian agro-processing by subsector, firm size and region

Variables	N	Technical efficiency	Scale efficiency
		Type of product	
Bakery	32	0.3493	0.9087
Beverages	14	0.5868	0.7893
Milling	31	0 .3753	0 .7750
Meat processing	9	0 .5426	0 .8761
Other agri-food	29	0.4469	0.7545
ANOVA F		1.67 ($p \leq 0.161$)	2.05 ($p \leq 0.093$)
		Number of workers	
Large ≥ 50	18	0.6904	0.8227
Medium > 10 & < 50	41	0.4051	0.9700
Small ≤ 10	56	0.3543	0.7025
ANOVA F		7.45 ($p \leq 0.001$)	18.17 ($p \leq 0.000$)
		Region	
Central	74	0.4929	0.7951
Northern	18	0.2193	0.8966
Western	23	0.3675	0.8234
ANOVA F		5.43 ($p \leq 0.006$)	1.24 ($p \leq 0.293$)

The final set of ANOVA tests revealed that there was no significant difference in scale efficiency across the regions, but then one would not necessarily expect that scale was closely correlated to the cost of doing business in remote areas. On the side of pure technical efficiency, the Central Region was significantly more efficient than either the Northern or Western outlying regions. In line with McPherson (1998) and Bonfiglio (2006), this result implies that there might be gains from improving business infrastructure in Zambia's outlying regions, especially in the Northern Region, which is the least developed part of the country. The reasons for such differences could be many, including transportation costs and proximity to the market (Krugman 1991).

The final Tobit models in Table 4 and the preliminary models in Appendix II combine the little available data on firm characteristics to explain the variations in the sector's technical efficiency performance. Possible explanations include a firm's degree of technical sophistication, as proxied by its capital/labour ratio; possible economies of scale, as measured by the number of workers it employs; whether the firm is right-sized for the technology, as captured by its scale efficiency score; and if it produces new knowledge through an in-house R&D programme. To fit this final model, the sample was partitioned into large and small-scaled operations, using a workforce of fifty employees as cut-off. We had $n = 52$ observations with which to fit the small-scaled model. A statistically significant Wald's LR test statistic and a McFadden's pseudo R-squared value of 0.2884 indicate that data from the small-scale cohort of firms produced an adequate fit. In this case, technical efficiency benefits marginally from a higher capital-labour ratio and is reduced significantly by more employees. Since most of these firms are approximately right-sized for the technology that they employ, right-sizing was not a helpful explanation for the variation in technical efficiency. The R&D dummy variable was unhelpful too, as none of these small-scaled operations have R&D expenses.

Table 4: Tobit models explaining pure technical efficiency scores for small- and large-scale agro-processing firms in Zambia

	Small scale		Large scale	
Explanatory variables	**Coefficient**	**SE**	**Coefficient**	**SE**
Capital labour ratio	0.0289 †	0.0197	0.0526 ***	0.0141
Workers (#)	-0.0175 *	0.0083	0.0010**	0.0003
Capacity utilisation	-0.2172	0.2051	-1.3687 **	0.4921
D in-house R&D			0.2620 †	0.1811
Constant	0.4254**	0.1325	1.4481 **	0.4808
Observations	52		63	
Wald's LR statistic	8.68 **		38.45 ***	
McFadden's pseudo R^2	0.2884		0.7617	

*** $p \leq 0.001$, ** $p \leq 0.05$, * $p \leq 0.10$, † $p \leq 0.15$

With a McFadden's pseudo R-squared of 0.7617 and a LR statistic of 38.45, the technical efficiency model for large-scaled firms performed even better that the model that explained technical efficiency levels amongst small-scaled firms. For this cohort, the sample size was n = 63. Here we see that technical efficiency is enhanced by more capital-intensive production, a larger scale of operation – provided that it takes place at the right scale, and with the presence of an in-house R&D programme. The negative sign on capacity utilisation was perplexing, as it suggests that firms that operate at the correct scale for their particular plant are less technically efficient than firms that are still struggling to achieve optimal capacity utilisation. Complacency provides the only reasonable explanation: firms that may already have achieved the optimal capacity utilisation might become a little lax technically, while those that are not there yet could still be scrambling to make ends meet. However, this explanation seems implausible, because it is unlikely that technically good managers would not also be able to reap scale benefits, and vice versa.

4. Conclusion

Agro-processing is the largest subsector within Zambian manufacturing, but the associated low technical efficiency levels poses huge challenges for the industry's competitiveness and future growth. Rising imports of processed food products speak to the lack of the necessary capabilities needed to meet the high food standards being demanded by the growing middle class. Meeting these standards will require that firms upgrade and become more dynamic and innovative in food quality, packaging and branding (Perez 2015). Thus, efforts to revitalise manufacturing will not yield significant results if firms are not encouraged to adopt new technologies through meaningful investments in both R&D and staff development. In this regard, sound public policy would be critical in harnessing public and private capital to create effective networks and social capabilities by linking small-scale producers to large-scale enterprises to achieve sector-wide competitiveness (Harper & Finnegan 1998; Shiferaw 2009; Perez 2015).

It is not surprising to find that small-scale firms are less efficient than larger scale operations, but the importance of small-scale firms to industrial growth goes beyond just being a seedbed for young entrepreneurs, whose success guarantees economic development (Jovanovic 1982; Lundvall & Battese 2000). Therefore, support aimed at enhancing the performance of small-scale firms remains crucial to Zambia's agro-processing industry. Creating an enabling business environment focused on reducing business costs, which remain prohibitively high in Zambia, would not only enable the small-scale sector of the industry to flourish, but would also allow for the appropriation of scale economies.

Finally, the study highlights the fact that regions with relatively well-developed infrastructure and a high population concentration are associated with high-performing firms. One implication is that there is a need for infrastructure development in the rural parts of Zambia. This will help reduce the business costs, such as those of transport, and provide rural-based agro-firms with access to regions with large markets.

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Appendix I: Distribution of firms by size (number of workers) and sector

ISIC_REV4	Description	Large	Medium	Small	Total
1010	Processing and preserving of meat	4	3	2	**9 (7.8%)**
1020	Processing and preserving of fish, crustaceans & molluscs		1	3	**4 (3.5%)**
1040	Vegetable and animal oils and fats		3	5	**8 (7%)**
1050	Dairy products		1	1	**2 (1.7%)**
1061	Grain mill products	6	6	19	**31 (27%)**
1062	Starches and starch products			6	**6 (5.2%)**
1071	Bakery products	1	17	14	**32 (27.8%)**
1072	Sugar	1			**1 (0.9%)**
1073	Cocoa, chocolate and sugar confectionery		1		**1 (0.9%)**
1079	Other food products not elsewhere classified	3	2	1	**6 (5.2%)**
1080	Prepared animal feeds		1		**1 (0.9%)**
1101	Distilling, rectifying and blending of spirits	1	2		**3 (2.6%)**
1102	Wines		1		**1 (0.9%)**
1103	Malt liquors and malt	2	3		**5 (4.4%)**
1104	Soft drinks, mineral waters, other bottled waters			5	**5 (4.4%)**
	TOTAL	**49**	**14**	**52**	**115 (100%)**

Appendix II: Tobit regression results

	Dependent variables	
Explanatory variables	**Technical efficiency**	**Scale efficiency**
Model I		
Medium-scale firms	-0.224 (0.088) ***	0.143 (0.058) **
Small-scale firms	-0.187 (0.091) **	-0.171 (0.0605) ***
Market share	0.341 (0.131) ***	0.032 (0.086)
Northern Region	-0.231 (0.084) ***	0.223 (0.055) ***
Western Region	-0.058 (0.074)	0.066 (0.049) ł
Constant	0.599 (0.083)	0.797 (0.055)
Log likelihood	-25.239	22.328
Pseudo R^2	0.357	15.413
Prob > chi^2	0.000	0.000
Model II		
Bakery sector	-0.057 (0.080)	0.171 (0.059) ***
Milling sector	-0.020 (0.082)	0.046 (0.06)
Meat processing	0.054 (0.119)	0.098 (0.088)
Beverages sector	0.132 (0.102)	0.021 (0.075)
Average labour cost	0.000 (0.000) ***	0.000 (0.000) *
Foreign labour (dummy)	0.065 (0.078)	0.098 (0.057) *
Constant	0.343 (0.064)	0.704 (0.047)
Log likelihood	-28.905	5.976
Pseudo R^2	0.264	4.858
Prob > chi^2	0.002	0.020
Model III		
Medium-scale firms	-0.215 (0.087) **	0.13 (0.059) **
Small-scale firms	-0.163 (0.091) *	-0.148 (0.062) **
Market share	0.208 (0.149) ł	
Bakery sector		0.156 (0.058) **
Northern Region	-0.207 (0.08) ***	0.214 (0.053) ***
Average labour cost	0.000 (0.000) *	0.000 (0.000)
Foreign labour (dummy)		0.0398 (0 .053)
Constant	0.541 (0.085)	0.762 (0.059)
Log likelihood	-23.752	24.615
Pseudo R^2	0.395	16.889
Prob > chi^2	0.000	0.000

*** significant at 1%, ** significant at 5%, * significant at 10%, ł significant at 20%

Note: Numbers in parentheses are asymptotic standard errors