# The Hazards of Small Firms in Southern Africa

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*Small enterprises are a ubiquitous feature of the economies of many developing countries. This study is the first to examine the duration of their survival using economic theory and modern econometric techniques. Using data sets from surveys conducted in four southern African countries, I estimate a proportional hazards model describing the closure rates of a sample of approximately 21,000 firms. There is an inverse relationship between enterprise growth rates and the closure hazard. The sector where it operates influences the hazard, as does its location. In some countries female-headed firms are at a survival disadvantage compared to their male counterparts.*

## I. INTRODUCTION

Some of the most pressing concerns of policy-makers in developing countries involve issues of employment generation. In many countries, labour force growth has outstripped the rate of job creation in the public sector, the 'modern' sector, and even the agricultural sector. Consequently, an ever-increasing number of workers are turning to the micro and small enterprise (MSE) sector[1] for a substantial part of their livelihood. Governments and donor institutions are beginning to realise the increasing importance of the MSE sector for income generation as well as for making the income distribution more equitable.

The MSE sector in most developing countries is extremely dynamic, with new firms being started, existing firms changing, and others closing down. Net employment growth depends on all of these factors, and yet until recently no data existed to permit a serious study of them. Using data from five southern and eastern African countries, Mead [*1994*] discusses net

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employment growth (that is, employment growth from start-ups of new firms plus employment growth from expansion of existing firms less employment loss due to closures), and its implications for policy-makers. McPherson [*forthcoming*] considers factors leading to growth of existing firms. Unfortunately, very little is understood about the factors which influence the duration of firm survival; indeed, this issue has not been studied in developed countries. An improved understanding of firm closure could greatly enhance the ability of governments and assistance agencies to promote MSEs. This paper attempts to fill some of that void by examining which characteristics of a MSE and its proprietor lead to survival of the enterprise, and which lead to closure. To this end, a unique set of data involving over 21,500 MSEs in four southern African countries is examined using an analysis technique which has until now not been used to study firm dynamics.

The following section presents what theory exists on enterprise dynamics, and buttresses this theory with some observations from past empirical studies. Section III explains one method of analysis useful for studying enterprise survival – hazard modelling – and section IV describes the data. Section V presents and interprets the results. A final section provides some conclusions and suggests directions for future research.

## II. THEORIES AND HYPOTHESES

Early examinations of firm behaviour primarily involved simple comparative statics. Subsequently, attempts were made to explain the evolution of market structures: these fall under the rubric 'stochastic theory'. In this class of models, a firm is assumed to draw each period from some distribution a value for the upcoming period's costs. Should the firm repeatedly be 'lucky' and have low-cost draws, it will grow and survive. These models were based on the stylised fact that firm growth and firm size are independent. The results of the stochastic models gave a theoretical base to this observation, frequently called Gibrat's Law. Empirical studies by Hart and Prais [*1956*] and Simon and Bonini [*1958*] found evidence supporting Gibrat's Law, at least among larger firms in the United States and Great Britain. Later studies found serious fault with the earliest versions of stochastic theory, both in terms of the assumptions of the theory, and the observed facts about business dynamics. Particularly damning was the finding that firm growth and firm size seemed to be inversely related. Some attempts were made to explain away this stylised fact, in particular by Mansfield [*1962*], who claimed that if the exit of smaller, slow-growing firms were allowed for, Gibrat's Law would still obtain. Lucus [*1978*] introduced differential levels of managerial ability into the model, but continued to assume that Gibrat's Law operates.

Still, none of these theories allows for uncertainty, and none of them is truly dynamic. More recently, attempts have been made to come up with a new theoretical framework which could incorporate these considerations. The most important such contribution is the 'learning model' of Jovanovic [*1982*]. In the learning model, firms are assumed to possess an innate and immutable cost parameter. This parameter can be thought of in several possible ways, perhaps most clearly as the level of managerial ability of the firm's proprietor. Although the distribution of this parameter for all firms is known to each firm, each firm is unsure of its own true cost. In addition to costs stemming from managerial inefficiency, firms also face randomly occurring costs in every period. As each period passes, a firm updates its beliefs about its true managerial ability based on the previous period's profits and costs. If at any time these beliefs imply that the firm's expected return will be less than the returns from the next best alternative, the firm will exit the industry. If a firm's true cost is low, it is likely that the update that it receives will be positive, and the firm will survive and grow. If, on the other hand, a firm is actually inefficient, the evidence will eventually lead the firm to exit. Put simply, inefficient firms decline and exit, while efficient firms survive and grow. Pakes and Ericson [*1987*] describe this process as the industrial organisational equivalent to Darwin's theory of natural selection.

Jovanovic's model implies two testable hypotheses which are pertinent to the study of enterprise closure:

(1) A firm's probability of closing will be decreasing in size. This is the case because bigger firms are more likely to have received positive clues about their true costs and have survived already – the inefficient firms are likely to have perished already. Empirical studies of enterprises in Nigeria, Sierra Leone, Colombia, the Philippines and the United States provide support for Jovanovic's predictions.[2]

(2) Enterprise closure rates should decrease with growth rates, since firms with higher growth rates tend to be larger. Growth represents, in some sense, success, and implies that the enterprise must have received positive clues about its true efficiency level. Phillips and Kirchoff [*1988*] find that this inverse relationship holds for small businesses in the United States.

While an improvement over earlier attempts to understand the dynamics of industries, the learning model is not without its shortcomings, and as such it appears able only to offer general guidance to the researcher of small enterprises in a developing country context. First, the cost parameter cannot be changed. If we think of this parameter as measuring managerial ability, its immutability implies that the multitude of training programs over the years for developing country entrepreneurs have been in vain.[3] Secondly, the empirical implications of the model, while quite testable, are very general. The researcher is given little guidance as to the specific sorts of variables that might influence growth and survival of firms. It is possible that Jovanovic's model could be extended to account for some of the observed regularities which are noted below; however, this is beyond the scope of the present article.

Since this study proposes no new theory, for further clues about these variables it is useful to consider the results of several empirical studies. The type of business in which an enterprise is engaged may exert some influence over its probability of closure. Phillips and Kirchoff [*1988*] cite studies of small firms in the United States that demonstrate differences in closure rates across sectors, with the highest rates in construction, manufacturing and retail trade. Other evidence from Nigeria also points to sectoral differences in firm closure rates [*Frishman, 1990: 15–17*].

It may also be the case that the location of an enterprise may help explain its life span. Cortes, Berry and Ishaq [*1987*] suggest that enterprises located in urban areas may face different closure probabilities than their rural counterparts. This may be a result of differences in demand conditions, degree of competition, or ability to procure inputs.[4] Strassmann [*1987*] suggests that home-based enterprises in commercial areas generate more income than similar enterprises in more remote areas. Additionally, other spatial effects may influence the chances of closing, for some of the same reasons. First, the type of business premise (for example, in the home, in a shop in a commercial district, mobile) may matter. A second aspect along these lines that bears consideration is the country in which the enterprise is located. Country-specific macroeconomic conditions, as well as historical, political and cultural factors may influence business closure.

With respect to the gender of the proprietor, Downing [*1990*] speculates that since a larger proportion of female-earned income goes towards supporting the family than that earned by males, female proprietors are, on average, more cautious. They are, Downing believes, more likely to diversify into other business activities. If female entrepreneurs are more cautious, then it may be that the chances of their enterprises closing are lower than those of males. On the other hand, being female may lead to a higher probability of closure if discrimination against women is prevalent.

It may also be the case that the ways in which MSEs are linked with other businesses, both upstream and downstream, have an impact on the closure rates. According to Mead [*1992*], increased specialisation can lead to an increased expected return (and thus better survival chances). However, it may also imply a new set of risks, which come about from an increased reliance on persons and businesses outside the enterprise. For example, when a fully-integrated weaver of grass mats or baskets begins to specialise in the weaving aspect, she will be able to produce more, and possibly better quality, output than when she also had to harvest the grass herself. However, she now depends on other people for her input supply. Due to data limitations, these issues will be explored in Appendix A for a subset of MSEs.

In summary, this research examines the following hypotheses, which come both from theoretical and empirical sources:

(1) Enterprise size, as well as enterprise growth rates, are inversely related to the probability of closing.

(2) Closure rates vary by sector.

(3) The location of the enterprise, especially whether it is urban-based or rural, influences its probability of closing.

(4) The linkages of MSEs with their customers and suppliers have an influence on the probability of closure.

(5) The gender of the proprietor is a significant determinant of the survival chances of an enterprise.

## III. HAZARD MODELLING

While there are other ways to study the survival patterns of MSEs, one highly attractive method for analysing this aspect of firm behavior is known as duration, or hazard modelling. To date, this technique has never been employed to examine firm survival in either developed or developing countries.[5] Hazard models were initially employed by industrial engineers and biostatisticians. More recently these models have been used by social scientists studying such events as recidivism, divorce and job tenure. In economics, most uses of duration and hazard modelling study spells of unemployment.[6]

One important difficulty in studying survival patterns of firms is that there will generally be enterprises in the data set which have not yet closed (incomplete observations are referred to as 'censored'). Given that 80 per cent of the observations in these data sets are censored, handling this problem is quite important. The censoring phenomenon is dealt with quite easily by hazard models. In this class of models, the dependent variable can be thought of as the probability that a firm closes, given that it was still alive at the beginning of the period. This conditional probability, the hazard rate, is defined in discrete time as follows:

$$h(t_i) = \frac{p(t_i)}{S(t_i)} \tag{3.1}$$

where

$h(t_i)$ = discrete-time hazard rate
$p(t_i)$ = probability of firm i closing between times t+1 and t
$S(t_i)$ = probability that firm i survives until time t

The hazard is easily estimated by dividing the number of closures in the sample by the number of firms which were in the 'risk set'. The risk set is made up only of those enterprises which are at risk of closing, that is, those which have not already closed. For example, if 1,000 enterprises have survived until their third year, and 100 of them close during that year, the estimated hazard rate for firms in their third year is 0.1. The estimated hazard rate can be thought of as the probability of closing during the period conditioned on being in the risk set.[7] Hazard models can be in discrete or continuous time, and parametric or non-parametric approaches are available for each.[8]

If data-entry and computational constraints are binding, it may be wise to consider a continuous-time method. In this case, the hazard rate would effectively be the probability of a firm closing during some arbitrarily small period:[9]

$$h(t) = \lim_{s \to 0} p(t,t+s) / S(t) \tag{3.2}$$

where

$p(t,t+s)$ = probability of a firm closing between t and t+s, and
$S(t)$ = probability of a firm surviving until time t.

Allison [*1984*] asserts that analysing data using a continuous-time framework will yield results quite similar to those from a discrete-time model. This being the case, it is in large part the size of the data-set that should determine which model to use. Given that the data sets which will be examined here involve several thousand observations, the continuous-time approach will be followed.

One of the most widely used hazard models is known as the proportional hazards model. Its popularity stems from its relative simplicity and flexibility. The proportional hazards assumption implies that the ratio of any two individuals' hazards is a constant regardless of time.

The hazard rate for this model can be expressed as:

$$h(t|x) = h_0(t)\, g(x, \beta) \tag{3.3}$$

where x is a vector of possibly time-varying characteristics, and ß is a vector of coefficients. In this expression, $h_0(t)$ can be thought of as the hazard rate when $g(x, \beta) = 1$. $h_0(t)$ is generally known as the 'baseline' hazard. While $g(X, \beta)$ can be any function of the data, it is commonly assumed that

$$g(x,\beta) = \exp(x\,\beta)\,, \tag{3.4}$$

which gives:

$$h(t|x) = h_0\,(t)\,\exp\,(x\beta)\,, \tag{3.5}$$

Theory may give the researcher a reason to assume a particular distribution for the baseline hazard, most commonly the Weibull, exponential, log-normal, or Gompertz. Cox [*1972*] suggests a more flexible approach, which allows for the estimation of the coefficients without resorting to any assumptions about the baseline hazard.[10] This is achieved by means of a 'partial likelihood' technique.[11] The partial likelihood is the product over all closures:[12]

$$L = \prod_{i=1}^{N} \frac{\exp\,(x_i\beta)}{\sum_{j\in R(t_i)} \exp\,(x_j\beta)} \tag{3.5}$$

The log-likelihood can be maximised numerically to provide estimates of the coefficients. While such estimates are less efficient than those which might be produced by maximising the likelihood function simultaneously with respect to $h_0(t)$ and ß, Efron [*1977*] shows that under fairly general conditions, this efficiency loss is not great.

Given an estimate of the coefficient vector, one can also estimate the baseline hazard, or equivalently, the survivor function. Such computations would, for example, permit estimates of the hazard itself for enterprises with certain characteristics. Given the nature of our data collection approach, and the potential biases resulting from it, only the estimates of the coefficients will be considered in this article. The nature of these biases will be examined in the Appendix.

## IV. THE DATA

### *Introduction*

The data were generated from country-wide surveys of the Kingdom of Swaziland, Botswana, Malawi and Zimbabwe, conducted in 1991 and 1992. Information on existing and closed micro and small enterprises was collected, yielding over 2,700 usable observations from Swaziland, approximately 1,300 from Botswana, over 12,000 from Malawi and just under 5,800 from Zimbabwe. These data are unique: before these surveys, no information about MSEs on a national level in these countries existed with respect to currently operating enterprises, and no data of any kind were available regarding now-closed MSEs.

Each of the surveys involved a random cluster sampling technique. Briefly, the countries were stratified (usually into rural areas, smaller towns and urban areas), and within each stratum, census enumeration areas were selected at random. Enumerators visited every household and shop within the selected areas. Any person who was operating a business at the time of the survey was interviewed, as were all persons who once ran a business which was no longer in operation at the time of the survey. Details on each of the surveys can be found in Daniels and Fisseha [*1992*], Daniels and Ngwira [*1993*], Fisseha and McPherson [*1991*] and McPherson [*1991*].

*Heterogeneity*

The proportional hazards specification is attractive in large part because of its flexibility. Since no assumptions are made about the baseline hazard, the estimates of the coefficients will not suffer from bias due to a misspecification of the baseline. There remain, however, some concerns about heterogeneity. Heterogeneity occurs when different categories of enterprises have different distributions of the hazard. The inclusion of independent variables is an attempt to control for the problem. Nevertheless, in the present case, there are almost certainly some variables that have been omitted. For example, profitability of the enterprise, changes in input and output prices faced by the firm, and levels of entrepreneurial human capital all seem likely to influence hazard. Unfortunately, such data are not available. This means that there remains some heterogeneity for which the model does not control. Struthers and Kalbfleisch [*1986*] examined the impact of omitted variables in the proportional hazards framework. They found that the coefficients estimated will be asymptotically biased towards zero, with the bias small unless the coefficients of the omitted variables are large. While they do not prove it, the authors speculate that the asymptotic variance of the coefficients that are estimated in the presence of omitted variables is smaller than it would be if all relevant variables were included. If this is the case, the impact on the t-statistics is ambiguous. In short, then, the absence of important variables will cause the coefficients that are estimated to understate the true impact of the included variables, and the reliability of the significance tests is called into question.

*Variables*

In order to test the hypotheses put forth above, a number of variables were used. The means and standard errors of each variable for each of the four countries are presented in Table 1.

To capture the impact of size on the hazard rate, the number of workers

TABLE 1

DESCRIPTIVE STATISTICS

| | Country | | | |
|---|---|---|---|---|
| Variable | Swaziland | Botswana | Malawi | Zimbabwe |
| | Mean and Standard Error | Mean and Standard Error | Mean and Standard Error | Mean and Standard Error |
| Average annual growth rate of employment, in percent | 8.42 (58.52) | 12.839 (42.740) | 10.810 (37.394) | 7.620 (31.806) |
| Number of workers in MSE at close or time of censoring | 2.00 (3.10) | 2.855 (5.143) | 1.978 (2.581) | 1.862 (2.843) |
| SECTORAL FACTORS | | | | |
| Dummy variable for MSEs in the manufacturing sector | .392 (.488) | .250 (.433) | .263 (.440) | .593 (.491) |
| Dummy variable for MSEs in the service sector | .064 (.245) | .095 (.294) | .046 (.209) | .060 (.238) |
| LOCATIONAL FACTORS | | | | |
| Dummy variable for MSEs located in commercial districts | .402 (.490) | .147 (.355) | .546 (.498) | .156 (.363) |
| Dummy variable for MSEs located along roads or paths | .054 (.226) | .051 (.221) | .057 (.231) | .031 (.174) |
| Dummy variable for MSEs that are mobile | .116 (.321) | .089 (.285) | .092 (.288) | .106 (.308) |
| Dummy variable for MSEs located in urban areas | .809 (.393) | .777 (.417) | .693 (.461) | .666 (.472) |
| PROPRIETOR CHARACTERISTICS | | | | |
| Dummy variable for MSEs with female proprietor(s) | .791 (.406) | .697 (.460) | .385 (.487) | .720 (.449) |
| Dummy variable for MSEs with mixed-gender joint proprietorship | .025 (.158) | .094 (.292) | .017 (.131) | .018 (.132) |
| OTHER ENTERPRISE CHARACTERISTICS | | | | |
| Dummy variable for MSEs which have received credit from formal sources | .028 (.165) | .095 (.293) | .045 (.208) | .020 (.138) |
| Dummy variable for MSEs which have received credit from informal sources (friends, family, moneylender) | .182 (.386) | .068 (.252) | .190 (.392) | .125 (.331) |
| SAMPLE SIZE | 2,707 | 1289 | 11,728 | 5,792 |

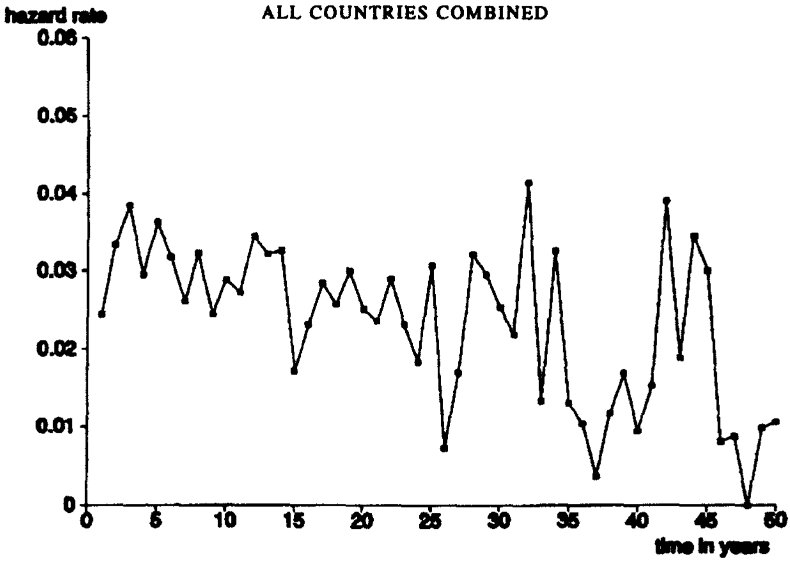
in the enterprise at the time of closure or censoring was used. The growth of the enterprise was measured as the average annual percentage growth in employment.

To capture variation in the hazard across sectors, two dummy variables representing sectors at the 1-digit International Standard Industrial Classification (ISIC) level are included. The excluded category, to which the sectoral variables will be compared, is trading.

Locational aspects are modelled with three sets of dummy variables. The first set uses the information that MSEs are located either in the home, in commercial areas, along roads (but not in commercial areas), or they are mobile. The reference category is home-based MSEs. A dummy variable for urban-based enterprises constitutes the second type of locational variable. The third type is composed of dummies representing locations in the ecological zones found in each country (four in Swaziland, five in Zimbabwe; these data were not available for Malawi and Botswana).

Proprietor gender is controlled for by means of two dummy variables, one taking on the value of one if the proprietor is female (or more than one female), and the other taking on the value of one for joint proprietorships with at least one proprietor of each gender. The base category is male proprietors. Other dummies model whether the enterprise had access to credit, either formal or informal.

FIGURE 1
SIMPLE HAZARD RATES
ALL COUNTRIES COMBINED



## V. RESULTS

### *Descriptive Statistics*

To get a sense of the level of the hazard rate in the countries in question, it is instructive to examine the simple hazard rate (that is, before controlling for the independent variables). Figure 1 presents a plot of the hazard rate for different survival times for all four countries.[13] Although the variance is fairly high, the graph shows that hazard rates for young firms are generally between 0.03 and 0.04, but show a steady downward trend until they have survived for approximately 25 years. The hazard rate briefly reaches levels even higher than those faced by the newer firms. Firm closures at this time may be largely by personal choice, since proprietors have themselves reached middle age and may be in a position to pursue other undertakings. The hazard rate again declines, but another spike occurs just after 40 years. Closings of firms of this vintage may be due to the retirement of the proprietor, or to her old age or closing health.

It is also interesting to look at the simple hazard rate for a given year stratified by various characteristics. These data are presented in Table 2. In all cases, female-run firms have a higher simple hazard rate than male-run firms. MSEs involved in trading have the highest hazard rates, while firms in the service sector have the lowest. MSEs based outside of the home and those in urban areas have lower hazard rates than home-based enterprises and MSEs in non-urban areas, respectively.

### *Interpretation*

The results of the hazard regressions are reported in Table 3.[14] Each coefficient is the partial derivative of the log of the hazard function with respect to the associated regressor. Interpreting the coefficients, then, involves exponentiating them. For example, the coefficient for the urban dummy variable for Swaziland is -.211. Since exp(-.211) = .810, it can be said that the hazard for urban-based MSEs is 81.0 per cent of that of MSEs in the outlying areas, if other factors are held constant.[15] For continuous variables, such as the growth rate or the enterprise size, if $\beta$ is the estimated coefficient, $100[e^{\beta}-1]$ gives the percent change in the hazard for a unit change in the explanatory variable, other things equal. Table 3 presents the calculation of $\exp(\beta)$ along with the estimated coefficients and t-statistics. In the discussion which follows, it should be remembered that a negative (positive) coefficient implies that the regressor has the effect of lowering (raising) the hazard, or raising (lowering) the survival period.

### *Findings*

The results presented in Table 3 provide some insight into the hypotheses

TABLE 2

SIMPLE HAZARD RATES* BY ENTERPRISE CHARACTERISTICS

| Enterprise Characteristic | Swaziland | Botswana | Malawi | Zimbabwe | All Countries |
|---|---|---|---|---|---|
| Overall Hazard | .0356 | .0170 | .0304 | .0405 | .0333 |
| Female proprietor | .0361 | .0232 | .0569 | .0451 | .0458 |
| Male proprietor | .0340 | .0038 | .0160 | .0294 | .0192 |
| Manufacturing | .0284 | .0084 | .0217 | .0226 | .0226 |
| Service | .0136 | .0000 | .0024 | .0341 | .0130 |
| Trade | .0437 | .0243 | .0361 | .0765 | .0433 |
| Home-based | .0467 | .0200 | .0403 | .0373 | .0382 |
| Non-home-based | .0281 | .0109 | .0266 | .0486 | .0296 |
| Urban | .0295 | .0151 | .0256 | .0421 | .0300 |
| Non-urban | .0616 | .0243 | .0410 | .0376 | .0413 |

* The hazard rate varies according to the number of years an MSE has survived. For purpose of this table, the hazard in question is the hazard faced by firms in their second year of existence. The choice of time period is arbitrary; selection of a different year would affect the absolute numbers, but not the relative comparisons.

TABLE 3

PROPORTIONAL HAZARDS MODEL

| | Country | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Regressor | Swaziland | | Botswana | | Malawi | | Zimbabwe | |
| | Coefficient and T-statistic | $exp^{\beta}$ | Coefficient and T-Statistic | $exp^{\beta}$ | Coefficient and T-Statistic | $exp^{\beta}$ | Coefficient and T-statistic | $exp^{\beta}$ |
| Average annual growth rate of employment, in percent | -.043 ** (-10.120) | .958 | -.027 ** (-2.293) | .973 | -.041 ** (-14.330) | .960 | -.054 ** (-10.874) | .947 |
| Number of workers in MSE at close or time of censoring | -.004 (-.140) | .996 | .029 (.844) | 1.029 | -.024 * (-1.918) | .976 | .030 ** (2.353) | 1.030 |
| SECTORAL FACTORS | | | | | | | | |
| BASE CATEGORY: TRADE | • | • | • | • | • | • | • | • |
| Dummy variable for MSEs in the manufacturing sector | -.218 ** (-1.908) | .804 | -1.258 ** (-5.060) | .284 | -.986 ** (-18.178) | .373 | -1.299 ** (-18.089) | .273 |
| Dummy variable for MSEs in the service sector | -1.057 ** (-3.808) | .347 | -2.822 ** (-2.771) | .059 | -1.628 ** (-10.441) | .196 | -.982 ** (-6.262) | .375 |
| LOCATIONAL FACTORS[a] | | | | | | | | |
| BASE CATEGORY: Home-Based MSEs | • | • | • | • | • | • | • | • |
| Dummy variable for MSEs located in commercial districts | -.911 ** (-6.877) | .402 | -.767 * (-1.830) | .464 | -.519 ** (-9.870) | .595 | -.615 ** (-5.652) | .541 |
| Dummy variable for MSEs located along roads or paths | -.434 (-1.985) | .648 | .330 (.768) | 1.391 | -.062 (-.643) | .940 | -.679 ** (-3.140) | .507 |
| Dummy variable for MSEs that are mobile | .503 ** (3.922) | 1.654 | .598 ** (2.276) | 1.818 | .282 ** (4.355) | 1.326 | -.046 (-.474) | .955 |
| BASE CATEGORY: Non-Urban MSEs | • | • | • | • | • | • | • | • |
| Dummy variable for MSEs located in urban areas | -.211 * (-1.844) | .810 | -.453 ** (-2.311) | .636 | -.238 ** (-5.688) | .788 | -.146 * (-1.902) | .864 |
| PROPRIETOR CHARACTERISTICS | | | | | | | | |
| BASE CATEGORY: MSEs with male proprietors | • | • | • | • | • | • | • | • |
| Dummy variable for MSEs with female proprietor(s) | .063 (.440) | 1.065 | .229 (.842) | 1.257 | .475 ** (11.451) | 1.608 | .359 ** (6.205) | 1.432 |
| Dummy variable for MSEs with mixed-gender joint proprietorship | .623 ** (2.035) | 1.865 | -.469 (-.998) | .626 | .205 (1.286) | 1.228 | .348 (1.611) | 1.416 |
| OTHER ENTERPRISE CHARACTERISTICS | | | | | | | | |
| BASE CATEGORY: MSEs which have received no credit | • | • | • | • | • | • | • | • |
| Dummy variable for MSEs which have received credit from formal sources | .135 (.367) | 1.145 | -.408 (-.859) | .665 | -.459 ** (-8.985) | .632 | -.453 (-1.581) | .636 |

cont.

TABLE 3 (cont.)

| Regressor | Country | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Swaziland | | Botswana | | Malawi | | Zimbabwe | |
| | Coefficient and T-statistic | exp[1] | Coefficient and T-Statistic | exp[1] | Coefficient and T-Statistic | exp[1] | Coefficient and T-statistic | exp[1] |
| Dummy variable for MSEs which have received credit from informal sources (friends, family, moneylender) | .228 * (1.896) | 1.256 | .840 ** (3.186) | 2.316 | -.190 ** (-3.666) | .827 | -.017 (-.177) | .983 |
| SAMPLE SIZE | 2,707 | | 1289 | | 11,728 | | 5,792 | |
| R-SQUARE ANALOGUE | .312 | | .378 | | .291 | | .311 | |

1. Regional dummies were included in the regressions for Swaziland and Zimbabwe. These coefficients are not reported for purposes of brevity, but are available from the author upon request.

* = significant at the 90% level ** = significant at the 95% level

detailed in section II above. That firm size and hazard are inversely related is an outcome predicted by Jovanovic's 'learning' theory, and is supported by empirical work in several countries. It is surprising, then, that in Swaziland and Botswana the size of an enterprise seems to have no significant influence on a firm's survival chances, and in Zimbabwe the relationship is actually a positive one.[16] It may be that while bigness has some advantages, such as access to reliable input sources, increased consumer awareness of the firm and its products, and economies of scale, larger firms are more likely to be caught in regulatory nets. In addition, larger firms may be less efficient than their smaller counterparts.[17]

Not surprisingly, enterprises which grow most rapidly stand a lesser chance of closing, a finding which is in accord with the Jovanovic model. As Table 3 implies (see section 5.2), a one per cent increase in the average annual growth rate of employment implies between a 2.7 per cent decrease (Botswana) and a 5.3 per cent decrease (Zimbabwe) in the hazard, *ceteris paribus*. Growth seems to be an indicator of success.

Controlling for other factors, hazard rates do seem to vary by sector, with enterprises in the manufacturing sectors of all countries but Swaziland having hazard rates that are on the order of 30 per cent of those in the retail trade sector. In every country, MSEs in the service sectors are significantly less likely to close than retail-based MSEs.[18]

The third hypothesis, that the location of enterprises has an impact on survival chances also receives strong support. Enterprises in commercial districts in the four countries considered have hazards that are between 40.2 per cent (Swaziland) and 59.5 per cent (Malawi) of those of home-based MSEs. Mobile enterprises stand a significantly lower chance of surviving in Swaziland and Malawi than home-based MSEs. Zimbabwean MSEs which are located beside a road have lower hazards than MSEs located in the home. These results may indicate that the advantage of proximity to the demand source that firms in commercial districts have outweighs the disadvantage of the increased competition found there relative to MSEs run from the home. That mobile enterprises (at least in Swaziland and Malawi) are more likely to close than home-based enterprises may be the result of the physical costs of being constantly on the move, as well as harassment by police.[19]

The hypothesis that rural firms are more likely to close than their urban counterparts also receives support from all countries. Urban enterprises have hazard rates that are 81.0 per cent of those in rural areas in Swaziland, while the comparable figures are 63.6 per cent, 78.8 per cent and 86.4 per cent for Botswana, Malawi and Zimbabwe respectively. Perhaps this is because of the relative inability of rural enterprises to participate in markets near areas with the highest incomes.

As for the gender of the proprietor, female-run firms in Swaziland and Botswana are at no perceivable disadvantage relative to MSEs run by men, although it appears that Malawian and Zimbabwean MSEs run by women are more likely to close. As suggested above, the survival chances of female-run enterprises may depend on two competing factors: women may be more risk-averse than men, but they may face discrimination in their activities to which male entrepreneurs are not subjected. One possible explanation is that these factors balance each other in Swaziland and Botswana, while the discrimination effect outweighs the risk-aversion effect in Malawi and Zimbabwe.

Several other interesting findings emerge from our analysis. One of the more intriguing has to do with the relationship of enterprise survival and access to credit. Shortages of operating capital, and to a lesser extent investment capital, are frequently cited as possible constraints on the success of small enterprises. This analysis shows that access to formal credit sources only confers a particular survival advantage on MSEs in Malawi. Interestingly, Swazi and Batswana enterprises which have borrowed money from informal sources at least once in the past have hazard rates that are significantly *higher* than those MSEs which have never borrowed from any source. Apparently, having to resort to family, friends, or moneylenders for funds is the mark of a desperate enterprise.[20]

Harrell [*1980*] has suggested an R-square analogue for the proportional hazards model. The value of this statistic for these data, shown at the bottom of Table 3, ranges from 0.291 in Malawi to 0.378 in Botswana. The modest values of this statistic suggests that a significant amount of variation in firm hazard rates is not being explained by the data.

TABLE 4

THE INFLUENCE OF COUNTRY ON HAZARD: ZIMBABWE BOTSWANA, MALWAI AND SWAZILAND COMBINED

| Regressor | Coefficient and T-statistic | exp$^{\beta}$ |
|---|---|---|
| Firm Growth Rate | -.047 ** (-20.905) | .954 |
| Firm Size | .003 (.358) | 1.003 |
| SECTORAL DUMMIES | | |
| BASE CATEGORY: Trade | * | * |
| Manufacturing | -1.004 ** (-25.303) | .366 |
| Services | -1.345 ** (-13.405) | .261 |
| LOCATIONAL DUMMIES | | |
| BASE CATEGORY: Home-Based Enterprises | * | * |
| Market Locations | -.631 ** (-14.964) | .532 |
| Roadside Locations | -.226 ** (-2.765) | .798 |
| Mobile MSEs | .206 ** (4.286) | 1.229 |
| BASE CATEGORY: Non-Urban Locations | | |
| Urban Locations | -.232 ** (-7.084) | .793 |
| | * | * |
| BASE CATEGORY: Enterprises in Malawi | | |
| Dummy for Botswana | -.860 ** (-9.237) | .423 |
| Dummy for Zimbabwe | -.219 ** (-5.260) | .803 |
| Dummy for Swaziland | -.364** (-6.995) | |
| PROPRIETOR CHARACTERISTIC DUMMIES | | |
| BASE CATEGORY: Male Proprietorship | * | * |
| Female Proprietorship | .410 ** (11.515) | |
| Mixed Gender Joint Proprietorship | .302 ** (2.703) | 1.353 |
| OTHER ENTERPRISE CHARACTERISTICS | | |
| Access to Formal Credit Sources | -.302 ** (-3.011) | .739 |
| Access to Informal Credit Sources | -.057 (-1.352) | .945 |
| REGRESSION STATISTICS | | |
| Sample Size | 21,489 | |
| R-Square Analogue | .294 | |

TABLE 5
MACROECONOMIC PERFORMANCE BY COUNTRY

| Country | GNP/Capita 1991 (US $) | Growth Rate of GNP/Capita; annual average 1980-1991 |
|---|---|---|
| Botswana | 2,530 | +5.6% |
| Swaziland | 1,050 | +3.1% |
| Zimbabwe | 650 | -0.2% |
| Malawi | 230 | +0.1% |

*Source*: World Bank [*1993*].

### *The Impact of Country on Hazard*

The analysis so far has considered the four countries separately. While this stratification permits an examination of the impact of particular regressors on the estimated hazard of each country, it does not clarify the significance of the differences between countries. Such differences are to be expected: each country has unique cultural, political and economic characteristics. In order to examine any differences in the hazard caused by differences in country of location, the data were combined, and three dummy variables representing country were included. The results of this exercise are presented in Table 4. Not surprisingly, the results generally underline the findings discussed above. Of particular interest are the coefficients on the country dummy variable. MSEs in each of the countries are less likely to close than their counterparts in Malawi, holding other factors constant. Furthermore, MSEs in Botswana are the least likely to close, followed by those in Swaziland, Zimbabwe, and Malawi. While the data do not permit a detailed analysis as to the reasons for this ranking, one possibility involves differences in macroeconomic conditions. Indeed, as Table 5 shows, Botswana and Swaziland have had high rates of growth of GNP per capita between 1980 and 1991, while Zimbabwe's and Malawi's have been low or negative. This finding also fits with Mead [*1994*], who argues that an important determinant of net employment growth is the macroeconomic performance of the country in question.

## VI. CONCLUSIONS

Small and micro enterprises are an increasingly important part of the economies of developing countries. If policy measures are to be taken to assist MSEs, or at least 'level the playing field', an understanding of how these firms grow and change over time is crucial. This research is a step in the direction of such an understanding. The data-sets analysed in this article are themselves unique: no information about closed MSEs in the developing world is available. The application of hazard models to these data is also innovative. Not even in industrialised countries has this technique been applied in the study of business dynamics.

The results of this analysis add to the understanding of small enterprises in several ways. Counter to Jovanovic's theory of firm evolution, size and the probability of enterprise closure are (with one exception) not negatively related. Given this finding, it is interesting that closure hazard and growth rates *are* inversely related, as the theory postulates. This implies that Jovanovic's theory of firm survival may be inadequate for these particular sorts of enterprises.

In addition to testing some of the empirical implications of Jovanovic's theory, the results presented above add to the body of empirical evidence on firm survival. With respect to enterprise characteristics, the sector in which a firm is involved has an influence on its survival chances. As a general rule, manufacturing concerns and MSEs in the service sector are less likely to close than firms in the retail and wholesale trades. At a more disaggregated sectoral level, there is some evidence that food and beverage production and processing, textile and wearing apparel production, and personal services are generally the least likely sorts of MSEs to close.

Location, too, has a strong influence on firm survival. In particular, home-based enterprises seem to have higher hazards than most other premises. Urban-based enterprises face lower hazard rates as well, controlling for other factors. The results also suggest that overall macro-economic conditions in a country have an influence on a firm's survival chances. In particular, MSE hazard rates were significantly different across countries, with the lowest hazard rates generally being found in countries with the highest rate of growth of gross domestic product (GDP).

The relationship between access to credit sources and survivability is another interesting finding, and one which may have important policy implications. With the exception of those in Malawi, those enterprises which had received loans from the formal sector had no greater chance of surviving than those MSEs which had no access to credit of any sort. In Swaziland, enterprises which reported receiving loans from informal sources had a *higher* hazard than those without any credit access.

Considering the factors relating to the proprietor of the enterprise, it appears that female-run MSEs are at a disadvantage in terms of survival relative to enterprises with male proprietors in Malawi and Zimbabwe, although the data do not permit an understanding of *why* this might be. In

Swaziland and Botswana, female proprietors are not disadvantaged in this manner.

Specific policy recommendations based solely on these findings would be tenuous at best, and perhaps even dangerous. The data do show that firms that have grown, firms involved in manufacturing or services, firms operating outside the home, firms in urban areas, and firms run by men are often less likely to close. This does not mean, however, that only these firms should receive assistance. That these sorts of enterprises are more likely to close may be the result of some market imperfection and not the result of some firm-level inferiority or inefficiency. For example, firms that are located in rural areas or that have female proprietors may be more likely to close because of underdeveloped infrastructure or discrimination, and not because they are necessarily inefficient. This implies that decisions regarding which sorts of firms an assistance program should target should consider not only the results of this research, but also other information including the factors that lead to firm growth, the types of firms that tend to be more efficient and institutional factors.

These findings also provide some guidance for future research in this area. First of all, these findings should help to revise the theory of small enterprise dynamics. They point out the need for a new theory, perhaps specific to enterprises in developing countries. Second, the modest values of the pseudo R-square measure make it clear that future data collection efforts ought to be modified to attempt to capture some of the variables that were omitted from this analysis. High on this list would be measures of human capital embodied in the proprietor or workers of the firm. Amongst other things, such variables might be able to capture differences in entrepreneurial drive. In particular, longitudinal data collection exercises would appear to be important. Following a cohort of MSEs from birth until closure, although quite expensive, would provide the clearest picture of the factors influencing firm hazard.

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## NOTES

1. For purposes of this discussion, MSEs are those non-farm income-generating activities with 50 or fewer workers.
2. Figures reported in Liedholm and Parker [*1989: 18*].
3. Pakes and Ericson [*1989*] have extended the Jovanovic model to include the possibility of human capital investment. While this 'active learning' model is perhaps a step in the right direction, it seems to have few testable implications.
4. The empirical evidence on this point is somewhat contradictory, with some studies showing a higher mortality amongst urban enterprises, and some in which the opposite is true. See

Liedholm and Parker [*1989: 19*].

5. Only a paper by Behrman and Deolalikar (1989) examines exit behavior among firms in developing country. They do not, however, employ hazard techniques.
6. See Kiefer [*1988*] for a review of the hazard literature.
7. This definition of the hazard is true in discrete-time models.
8. If time is measured in discrete intervals, the model reduces to a simple dummy dependent variable framework, with the dependent variable taking on a value of zero for each period a firm is alive, and a value of one in the period in which the firm dies. While the discrete-time case is the simplest to understand, it becomes cumbersome if there are many firms in the sample, or if each firm lives many periods. For example, if there were 20,000 firms in a data-set each of which lived an average of five years, the total number of observations would approach 100,000. Should time be measured in months, the difficulties would be even more staggering.
9. Allison [*1984*] points out that while it may be useful to consider the hazard rate as an instantaneous probability of failure, it is actually a density.
10. Allison [*1984*] reports that the coefficient estimates emerging from the parametric models and those from a Cox proportional hazards model are typically quite close to one another. This implies that if one is interested primarily in the coefficient estimates, the choice of the model is relatively unimportant.
11. As Chung, Schmidt and Witte [*1990*] note, the likelihood is 'partial' since not all information is used. Specifically, only the order of survival times matters: the exact times of censoring or failure are not considered.
12. This partial likelihood function assumes that at every time at which failure occurs, only one enterprise fails. In principle, the probability of having more than one failure occur at a single point in time is zero in a continuous-time setting. However, 'ties' frequently occur in practice. If there are ties, the likelihood function becomes slightly more complex (see Lawless [*1982*]).
13. The figure presents a graph of the Kaplan–Meier estimates of the hazard rate.
14. The chi-square test rejects the hypothesis that the coefficients are not jointly significant in each country. The test statistics are 269.69 for Swaziland, 97.65 for Botswana, 1209.17 for Malawi, and 546.32 for Zimbabwe.
15. Similarly, $1/e^{\beta}$ represents the percent by which the hazard of the excluded group (non-urban firms, in this case) is different than the group for which the dummy variable equals one. For more detail, see Allison [*1984: 28*].
16. One could also measure size as the number of workers when the enterprise began its life. If initial size rather than size at close is used as a regressor, none of the coefficients or standard errors change significantly.
17. Evidence of the relative efficiency of small firms is presented in Liedholm and Mead [*1987*].
18. Each regression was also run with the sectoral dummies disaggregated to the 2-digit ISIC code level. While no clear pattern emerged from this exercise, the food and beverage production and processing, the textile and wearing apparel, and the personal services sectors had lower hazard rate than retail trade in three of four countries. These more detailed results are available from the author on request.

20\. In both countries, the 'hawkers' are required to have a license. In order to escape recognition by the authorities, and in order not to pay the license fee, many vendors avoid getting this license.

20\. Two points should be noted with respect to the credit variables. First, since very few people have access to credit in these countries, it would be hasty to make policy statements based on these results. Also, the data do not contain information on the purposes or uses of the credit. Such information might better explain the hazard than the variables used here.

## REFERENCES


Allison, Paul D., 1984, 'Event History Analysis: Regression for Longitudinal Event Data', *Sage University Papers*, Beverly Hills, CA: Sage Publications.

Behrman, Jere R. and Anil B. Deolalikar, 1989, ' ...Of the Fittest? Duration of Survival of Manufacturing Establishments in a Developing Country', *The Journal of Industrial Economics*, Vol.38, No.2 pp.215–26.

Chung, Ching-Fan, Schmidt, Peter and Ann D. Witte, 1990, 'Survival Analysis: A Survey', Draft paper, East Lansing, MI: Michigan State University.

Cortes, Mariluz, Berry, Albert and Ashfaq Ishaq, 1987, *Success in Small and Medium Scale Enterprises: The Evidence from Colombia*, New York: Oxford University Press.

Cox, D.R., 1972, 'Regression Models and Life Tables (with Discussion)', *Journal of the Royal Statistical Society*, series B, 34, pp.187–220.

Daniels, Lisa and Yacob Fisseha, 1992, 'Micro- and Small-Scale Enterprises in Botswana: Results of a Nationwide Survey', GEMINI Technical Report No.46, Bethesda, MD: Development Alternatives, Inc.

Daniels, Lisa and Austin Ngwira, 1993, 'Results of a Nationwide Survey on Micro, Small and Medium Enterprises in Malawi', GEMINI Technical Report No.53, Bethesda, MD: Development Alternatives, Inc.

Downing, Jeanne, 1990, 'Gender and the Growth of Microenterprises', GEMINI Working Paper No.5, Bethesda, MD: Development Alternatives, Inc.

Efron, Bradley, 1977, 'The Efficiency of Cox's Likelihood Function for Censored Data', *Journal of the American Statistical Association*, Vol.72, No.359, pp.557–65.

Fisseha, Yacob and Michael A. McPherson, 1991, 'Small Enterprises in Swaziland: Results of a Country-Wide Survey', GEMINI Technical Report No.24, Bethesda, MD: Development Alternatives, Inc.

Frishman, Alan, 1990, 'The Survival and Disappearance of Small Scale Enterprises in Urban Kano, 1973–1980', Draft paper, Geneva, NY: Hobart and William Smith Colleges.

Harrell, Frank, 1980, 'The PHGLM Procedure', *SAS Supplemental Library User's Guide*, Cary, NC: SAS Institute, Inc., pp.119–31

Hart, P.E. and S.J. Prais, 1956, 'The Analysis of Business Concentration: A Statistical Approach', *Journal of the Royal Statistical Society*, 119, Part 2, pp.150–91.

Jovanovic, Boyan, 1982, 'Selection and the Evolution of Industry', *Econometrica*, Vol.50, No.3, pp.649–70.

Kiefer, Nicholas M., 1988, 'Economic Duration Data and Hazard Functions', *Journal of Economic Literature*, Vol.26, No.2, pp.646–79.

Lawless, J.F., 1982, *Statistical Models and Methods for Lifetime Data*, New York: John Wiley & Sons.

Liedholm, Carl and Donald Mead, 1987, 'Small Scale Industries in Developing Countries: Empirical Evidence and Policy Implications', Michigan State University International Development Paper No.9, East Lansing, MI: Michigan State University.

Liedholm, Carl and Joan Parker, 1989, 'Small Scale Manufacturing Growth in Africa: Initial Evidence', Michigan State University International Development Papers, Working Paper No.33, East Lansing, MI: Michigan State University.

Lucas, Robert E. Jr., 1978, 'On the Size Distribution of Business Firms', *Bell Journal of Economics*, Vol.9, No.2, pp.508–23.

McPherson, Michael A., 1991, 'Micro and Small Scale Enterprises in Zimbabwe: Results of a Country-Wide Survey', GEMINI Technical Report No.24, Bethesda, MD: Development Alternatives, Inc.

McPherson, Michael A. (forthcoming). 'Growth of Micro and Small Enterprises in Southern Africa', *Journal of Development Economics*.

Mansfield, Edwin, 1962, 'Entry, Gibrat's Law, Innovation, and the Growth of Firms', *American Economic Review*, Vol.52, No.5, pp.1031–51.

Mead, Donald C., 1992, 'Micro and Small Enterprise Development in a Subsector Context: Increasing Specialisation, Decreasing Vertical Integration', *Small Enterprise Development*, Vol.3 No.1.

Mead, Donald C., 1994, 'The Contribution of Small Enterprises to Employment Growth in Southern and Eastern Africa', Draft Paper, East Lansing, MI: Michigan State University.

Pakes, Ariel and Richard Ericson, 1987, 'Empirical Implications of Alternative Models of Firm Dynamics', Madison, WI: University of Wisconsin, Social Systems Research Institute.

Phillips, Bruce D. and Bruce A. Kirchoff, 1988, 'Analysis of New Firm Survival and Growth', Conference Paper, Calgary, Canada: Babson Entrepreneurship Research Conference.

Simon, Herbert A. and Charles P. Bonini, 1958, 'The Size Distribution of Business Firms', *American Economic Review*, vol. 48, No.4, pp.607–17.

Strassmann, W. Paul, 1987, 'Home-Based Enterprises in Cities of Developing Countries', *Economic Development and Cultural Change*, Vol.36, No.1, pp.121–44.

Struthers, C.A., and J.D. Kalbfleisch, 1986, 'Misspecified Proportional Hazards Models', *Biometrika*, Vol.73, No.2, pp.363–69.

World Bank, 1993, *World Development Report 1993*, New York: Oxford University Press.

## APPENDIX A

While these data-sets are unique, they nevertheless have their shortcomings. It is instructive to consider the potential biases specific to the study of survival which may result from using retrospective data. It is possible, for example, that there is a systematic underreporting of past, closed enterprises. This could result for several reasons. Entrepreneurs may simply not remember having run a business in the past, particularly if it was long ago, or short-lived. It could also be the case that the respondent does not consider an especially short-lived venture worth reporting. In addition unpleasant events, such as a business closure, may not be remembered. Finally, if there is any stigma attached to having closed at a business, there may be incentive to not admit any such enterprises to the interviewer. Should any of these factors be significant, the reported number of closures would be less than the true number. Should one be interested in calculating the actual hazard rates from the data, this could represent a serious difficulty. Specifically, the calculated hazard rates would understate the true hazard.

If one is interested in the effect of various factors on the hazard rate, rather than the hazard itself, the above-mentioned underreporting bias would be problematic only if particular sorts of individuals are more likely to report enterprise closures than are others. For instance, if males are not as likely as females to admit to having had a business closure, the coefficients on the gender-based dummy variables may be incorrect. While there is no particular reason to believe that this is the case here, it is important to recognise the possibility.

## APPENDIX B

It may be the case that the ways in which MSEs are linked with other businesses, both upstream and downstream, have an impact on the closure rates. Mead [*1992*] hypothesises that while increasing specialisation may lead to an increased expected return, it also may imply new risks to the firm. For the current data, backward linkages are represented by a group of 4 dummy variables, which represent the five possible ways the MSE can procure its main input: by making or gathering it, by buying unprocessed raw materials, by buying semi-processed raw materials, by buying finished products for resale or by some other manner, with the buying finished products serving as the base category. Forward linkages are represented by a dummy variable taking on the value of 1 if the MSE sells directly to the final consumer, and 0 if it sells to an intermediate buyer. However, these measurements of linkages are appropriate only for MSEs involved in manufacturing; only these firms are considered in the following analysis. The results of this exercise are presented in Appendix Table 1.

In the case of backward linkages, there is some evidence that less specialised MSEs have better survival chances than their more specialised counterparts. This may indicate that the risks suggested by Mead [*1992*] that result from specialisation are important for small-scale manufacturers in these countries. As for forward linkages, there is no evidence that increased specialisation either increases or decreases survival chances. It is possible that the measures of these linkages contained in the data are inadequate. Future data collection efforts should consider these issues further.

APPENDIX TABLE 1

LINKAGE EFFECTS: SWAZILAND, MALAWI AND ZIMBABWE COMBINED

| Regressor | Coefficient and T-statistic | exp[a] |
|---|---|---|
| Firm Growth Rate | -.048 ** (-9.289) | .953 |
| Firm Size | .038 ** (3.908) | 1.039 |
| LOCATIONAL DUMMIES | | |
| BASE CATEGORY: Home-Based Enterprises | * | * |
| Market Locations | -.285 ** (-2.938) | .752 |
| Roadside Locations | -.005 ** (-.021) | .995 |
| Mobile MSEs | .372 ** (3.383) | 1.451 |
| BASE CATEGORY: Non-Urban Locations | | |
| Urban Locations | -.042 (-.646) | .959 |
| | * | * |
| BASE CATEGORY: Enterprises in Swaziland | | |
| Dummy for Zimbabwe | -.404 ** (-4.646) | .668 |
| Dummy for Malawi | -.021 (-.245) | .979 |
| PROPRIETOR CHARACTERISTIC DUMMIES | | |
| BASE CATEGORY: Male Proprietorship | * | * |
| Female Proprietorship | .719 ** (8.928) | 2.052 |
| Mixed Gender Joint Proprietorship | .479 (1.466) | 1.614 |

cont.

APPENDIX TABLE 1 (cont.)

| | | |
|---|---|---|
| **OTHER ENTERPRISE CHARACTERISTICS** | | |
| BASE CATEGORY: No Access to Credit | | |
| Access to Formal Credit Sources | -.179 (-.755) | .836 |
| Access to Informal Credit Sources | -.023 (-.274) | .977 |
| **LINKAGE CHARACTERISTICS** | | |
| BASE CATEGORY: MSE Buys Finished Products for Resale | * | * |
| MSE Makes or Gathers Most Inputs | -.486 ** (-3.273) | .615 |
| MSE Uses Primarily Unprocessed Inputs | .028 (.182) | 1.028 |
| MSE Uses Primarily Semi-Processed Inputs | -.320 ** (-2.377) | .726 |
| BASE CATEGORY: MSE's Main Customers Are Not Final Consumers | * | * |
| MSE Sells Mainly to Final Consumer | -.146 (-1.023) | .864 |
| **REGRESSION STATISTICS** | | |
| Sample Size | 7,577 | |
| R-Square Analogue | .209 | |