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Credit Can Precipitate Firm Failure: Evidence from Kenyan Manufacturing in the 1990s

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Abstract:

This paper models firm survival in Kenyan manufacturing with a particular emphasis on the effect of credit on firm resilience. The paper explores how firms coped with the challenging economic environment that prevailed in the 1990s particularly the effect of the dramatic increase in interest rates. The key finding is that the burden of past loans precipitated firm failure in the 1990s but overdrafts did not seem to have had a significant impact on firm failure. Furthermore, older firms appear to have resisted better than younger ones, but there is no evidence that large firms had higher survival rates. These results are robust to different specifications, namely probit models, Cox proportional hazard models and exponential, Gompertz and Weibull parametric hazard models. The main contribution of the paper is to highlight the role of credit in explaining firm failure in a shock-prone developing economy. The study shows that the key factors explaining firm survival in developed economies, namely size and age, are not necessarily the most relevant determinants of firm survival in developing economies. Methodologically, this paper is one of the few that have applied hazard analysis to firms in developing economies.

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1. Introduction

The 1990s were a very difficult period for Kenya's manufacturing. The climate of uncertainty about politics and economic policy may have induced entrepreneurs to adopt a wait-and-see attitude [Bigsten (2002)]. This suggests that firm survival is an appropriate question to raise, to explore how the manufacturing sector coped with the challenging economic environment in the 1990s particularly the dramatic increase in interest rates [see Nkurunziza (2004)]. In a comparable context, Andreff (1995) carries out survival analysis to determine the extent to which firms in Eastern Europe were able to cope with sudden liberalisation policies after the end of Communism in the late 1980s. This paper models firm survival over the 1990s, with a particular focus on the effect of credit on firm resilience.

This paper complements recent studies undertaken by researchers at the Centre for the Study of African Economies and the members of the ISA (Industrial Surveys in Africa) Group on related aspects of African manufacturing. These include Bigsten*, et al.* (2003) on credit rationing, Bigsten*, et al.* (1999a) on export of manufacturing, Bigsten*, et al.* (1999b) on investment, Harding*, et al.* (2004) on survival, Fafchamps (2000) on ethnicity and credit, Fafchamps (1999) on risk sharing and credit, and Fafchamps*, et al.* (2000) on inventories and risk in African manufacturing.

The paper finds that the burden of past loans precipitated firm failure. This is not surprising in view of the extent of interest rate and other macroeconomic shocks that hit the economy in the early 1990s. However, the use of overdrafts does not seem to have had a significant effect on firm survival. Furthermore, older firms appear to have resisted better than younger ones, but there is no evidence that large firms had higher survival rates. The non-significance of the size variable is surprising, but it should be noted that many studies have found contradictory results on the effect of size on survival [McPherson (1995), Mead and Liedholm (1998); Gort and Klepper (1982), Klepper and Simons (2000)]. These results are robust to different specifications, namely probit models, Cox proportional hazard models and exponential, Gompertz and Weibull parametric hazard models.

The main contribution of the paper is to highlight the role of credit in explaining firm survival in an unstable developing economy. Despite the widely shared belief that credit is an important factor explaining firm performance in these economies, there is little systematic empirical evidence on the subject [Fafchamps*, et al.* (1994); Fafchamps*, et al.* (1995)]. Moreover, although hazard models have become popular in the analysis of spells of unemployment, their application to the analysis of firm resilience in developing economies is still very limited. Furthermore, the study shows that age and size are not the key factors explaining firm survival in developing economies although they are the most important determinants of survival in developed economies.

This paper differs from Nkurunziza (2005a), which models the effect of credit on firm growth and convergence. Firstly, the two papers use two different methodologies to model two different phenomena, namely survival and growth. Secondly, the period of observation is different. Whereas Nkurunziza (2005a) covers the period from firm creation to 1999, survival analysis focuses on the crisis period from 1992 to 1999. Thirdly, this paper uses a different sample of firms. It studies both surviving and exiting firms, addressing the problem of selection bias identified in Nkurunziza (2005a).

The rest of the paper is organised as follows. Section 2 reviews the literature on the determinants of firm survival. Section 3 discusses the data and associated issues. Section 4 models firm failure as a dichotomous process. Section 5 models firm failure using hazard models. Section 6 concludes the analysis and suggests some extensions for future research.

2. The Determinants of Firm Survival

Analyses of firm survival in developed economies have focused on the determinants of entry and post-entry behaviour of firms. However, Audretsch and Mata (1995), and Geroski (1995) argue that understanding post-entry performance is more important than entry itself to explain the process of industry evolution. The distinction between entry and post-entry analysis arises from the "liability of newness" [Shepherd, *et al.* (2000)]. Our central interest is to analyse how credit affects firm survival post-entry.

Empirical studies in developed economies identify four key determinants of survival. These are size, age, technology and industrial characteristics. In a developing economy like Kenya, we posit that credit is equally if not more important than the other factors. Additional determinants discussed in the literature include geographical location, macroeconomic variables such as the stage of the business cycle, and the legal status of firms.

2.1. Credit Market Imperfections, Access to Credit and Firm Survival

If all firms had equal access to external financial resources credit would not have any effect on firm survival. The fact is that firms have unequal access to credit and even those with access may find credit to be very costly, limiting investment. In a cross-country study covering four African countries (Cameroon, Ghana, Kenya and Zimbabwe), Bigsten, *et al.* (1999b) conclude that high capital costs facing firms are the most important factor adversely affecting investment. If investment is essential for firm viability, firms that do not have access to affordable credit may be unable to meet the cost of required investments. As a result, the authors find a high correlation between investment and the level of profits, suggesting that firms depend on their own funds to finance investment. This is in line with the financial pecking order hypothesis [see Scholtens (1999); Brito and Mello (1995)] and the finding that firms in African manufacturing are credit constrained [Bigsten*, et al.* (2003)].

Whether credit is good or not for firm survival depends on the conditions under which it is used. Credit is helpful when it is accessible and reasonably priced. Otherwise, credit may have a negative impact on firm survival if depressed economic activity and high interest rates result in firm insolvency. For example, Ndung'u (1998) notes that after the dramatic increase in interest rates in the early 1990s in Kenya, expensive credit increased financial vulnerability of credit-dependent firms.

The channels through which credit may influence firm survival are diverse. First, from the creation of a firm, having access to credit may enable an entrepreneur to start a firm with an efficient size relative to entrepreneur without access to credit [Shorrocks (1988), Geroski (1995)]. For example, Bates (1990) finds that U.S. firms with the largest financial investments at start-up have the highest survival rates. Geroski (1995: 425) also notes that firms "having access to the deep pockets of a corporate parent operating in some other market …" have an advantage over their de novo entrant counterparts. These firms are less likely to fail during the first five to ten years post-entry.

Second, the limited capacity to raise external funds and the ensuing financial constraint may increase firm vulnerability. McPherson (1995) finds a positive and significant association between access to credit and firm survival in Malawi but the relationship is not significant in Botswana, Swaziland and Zimbabwe. The study's finding that small firms that had loans from informal sources had a higher hazard rate than those without any access to credit in Swaziland suggests that firms resorting to family, friends or moneylenders to borrow were the desperate ones that had become too weak to continue functioning.

Third, in many developing economies, firms compete for and attempt to keep good customers by offering trade credit [Fafchamps (1997)]. Such firms may need bank credit in the form of overdrafts to finance their own operations before their customers pay. In this regard, the liberalisation of interest rates and their ensuing rise made debt servicing more onerous in Kenya, putting many firms in difficulty. Firms that borrowed in the early 1990s were more likely to shrink and, presumably, to exit in the following years.

Fourth, firms relying on an imperfect credit market may become captive borrowers [Fisman and Raturi (2003)] and suffer rather than benefit from their exclusive relationship with lenders. This is particularly harmful when credit suppliers are banks with poor banking practices. Habyarimana (2003) provides an account of how bad practices of a number of banks in Uganda led to their collapse, which affected about 30 percent of manufacturing firms.

Fifth, credit can help inefficient firms to continue operating at the expense of more efficient enterprises. Nkurunziza and Ngaruko (2002) mention the case of Burundi where bank credit was used to momentarily save crumbling firms that had lost their self-financing capacity due to a major political and economic crisis in the 1990s. As political instability persisted and economic crisis deepened, a number of these firms eventually failed. Purcell (1990) also notes that in India, as a result of government controls on the banking sector, 14 percent of total bank credit to industry was tied up in "sick" firms in June 1986.[1]

In this light, Harris*, et al.* (1994) show that liberalisation of the financial sector in Indonesia in 1983 badly affected inefficient firms that had enjoyed an exclusive access to cheap government controlled credit. Liberalisation provided a level playing field that

[1] A sick firm was defined by Indian authorities as a firm registered at least seven years prior to the year when the industrial survey was made, had accumulated losses equal to or exceeding the sum of its paid-up capital and free reserves, and had suffered cash losses in the current and preceding year.

benefited the small new entrants while increasing exit of old firms. A positive result of liberalisation is that it increased productivity within the sector. Even in a developed economy like the United States, increases in productivity were the result of resource reallocation between exiting and more productive entrants [Olley and Pakes (1996)].

However, high productivity could also be the result of a lack of access to credit. Firms without access to external resources may face a binding budget constraint, forcing them to use resources more efficiently than firms with access to credit. To illustrate this point in the case of Kenya, the mean ratio of value added per output is 0.25 for firms using credit as opposed to a ratio of 0.34 for firms not using credit. These values are statistically different at 8 percent significance level.

Finally, large firms may use their privileged access to financial resources in a deliberate strategy to block entry or precipitate exit of smaller but more efficient firms. Tirole (1995) illustrates this case in his conceptualisation of "The long purse story" where financially powerful firms use their resources to reduce market prices below production costs in a bid to discourage the entry of potential competitors.

2.2. Other Determinants of Firm Survival

This section discusses briefly the other determinants of firm survival. These are size, age, technology, sector of activity and location.

2.2.1. Firm Size and Survival: Audretsch and Mahmood (1995: 97) note that the positive relationship between firm survival and both size and age is one of the most striking stylised facts regarding industry dynamics. Small size implies high average production costs that constrain firm profitability. Hence, firms growing fast attain quickly the minimum efficient scale (MES), increasing their probability of survival.[2] Geroski (1995) finds that it may take more than a decade for successful entrants to reach the size of the average incumbent. The implication is that large entrants have high survival rates [Ong (2001); Audretsch (1991); Audretsch and Mahmood (1995); Evans (1987a); Evans (1987b); Dunne*, et al.* (1989); Tschoegl (2002)] and their sizes are usually larger than the MES [Reynolds (1938)].

Whether the appropriate size to consider in empirical studies of firm survival is start-up or current size is an open question. Many studies use start-up size but other empirical studies argue that post-entry size is a better predictor of firm survival [Mata*, et al.* (1995)]. We use the latter measure in our analysis.

The stylised fact about the positive relationship between size and firm survival needs to be reconciled with the empirical observation of an asymmetric distribution skewed towards small size in many manufacturing industries. Agarwal and Audretsch (1999) use a homogeneity test to show that big size may help a firm survive in a highly uncertain period during the formative years of a product lifecycle. However, as technology becomes widely available and uncertainty declines in a product's mature period, small firms may be able to compensate for their size disadvantage by occupying strategic niches.

Empirical findings on African manufacturing show that the relationship between firm size and survival varies across countries. McPherson (1995) finds that size has no significant impact on firm survival in Botswana and Swaziland. In Zimbabwe, size has a positive impact on survival while it has a negative impact in Malawi. In a model where all four countries are pooled, size is not significantly related to firm survival. Furthermore, Mead and Liedholm (1998) find a negative relationship between size and survival in Africa. In developed economies, Klepper and Simons (2000) find that large size increases survival

[2] Klepper and Simons (2000) note, however, that economies of scale are quickly exhausted and cannot explain much of the cross-sectional variation in market structure.

only among technology users. Gort and Klepper (1982) find that it is efficiency not size that increases firm survival (see also Section 2.2.3 below). Hence, Harding*, et al.* (2004) conclusion that 'the main determinant of exit is firm size with small firms having much higher exit rates than large ones' does not seem to be consistent across economies.

2.2.2. Firm Age and Survival: The relationship between firm age and the probability of survival is explained on the basis of Jovanovic (1982) and Pakes and Ericson (1987) learning models discussed in Nkurunziza (2005a). However, in his study of Ethiopian manufacturing, Mengistae (1998) argues that the significance of the age variable does not necessarily mean that older firms are more efficient. Rather than efficiency, age may just capture the impact of good behaviour, signalling reputation and its effect on accessing inputs such as credit, as developed in Nkurunziza (2005b).

In a cohort of U.S. entrant firms analysed over the period 1963-1982, Geroski (1995) and Dunne*, et al.* (1989) find that 61.6 percent of the entrants exited within five years of entry and almost 80 percent of them within 10 years. In Africa, Mead and Liedholm (1998) find that 50 percent of firm closures take place within the first three years of start-up.

A less well researched aspect of firm survival refers to the 'outside opportunities' available for firm owners. Nafziger and Terrell (1996) find that in Southern India, an increase in the level of education of a founding entrepreneur reduces survival. Mengistae (1998) also finds that more schooling is associated with a low probability of self-employment in Ethiopia. The reason may be that education opens up more opportunities so an entrepreneur operating in a highly risky environment may prefer to opt for a fixed wage in the civil service or the private sector.

In contrast, Bates (1990) finds that age and education increase longevity of U.S. small businesses. This provides another illustration of the differences in the determinants of firm survival between developed and developing economies. More generally, empirical studies on both developed and developing economies have found a positive correlation between survival and firm age [Evans (1987b); Dunne*, et al.* (1989); Geroski (1995); Tschoegl (2002); Klepper and Simons (2000); Klepper (2002); Audretsch (1991); Mead and Liedholm (1998); McPherson (1995)].

2.2.3. Technology and Firm Survival: Klepper (2002) and Klepper and Simons (2000) find that it is through technology that age and size appear to be important determinants of firm survival. Using the case of the U.S. tire industry, the authors show that imitator entrants have low rates of survival than innovators. Moreover, in industries where innovative activity of small firms plays an important role in production, the rate of survival is low because entrants introducing new technologies force their less technology-intensive competitors to exit [Audretsch (1995)]. Klepper (2002) and Klepper and Simons (2000) find that when technology is controlled for, firm age loses its explanatory power.

Interacting the technology and size variables shows that small technology-intensive firms have a lower hazard rate than firms with comparable size and even some larger firms that use less efficient technologies. Klepper and Simons also show that size lowers the hazard rate only among technology users but not among non-users. In their analysis of the process of diffusion of product innovations, Gort and Klepper (1982) show that only the most efficient firms survive but there is no evidence that these are the largest firms. Therefore, the expected relationship between technology and survival is positive.

2.2.4. Industry Characteristics and Survival*:* Survival rates vary across industries. In Africa, the studies by McPherson (1995) and Mead and Liedholm (1998) suggest that sectoral variables are important determinants of firm survival. In U.S. manufacturing, Audretsch (1991) finds that by 1986, the survival rate over a period of ten years exceeded 40 percent in sectors like paper, non-electrical machinery, and primary metals, while the rate remained below 27 percent in the petroleum, apparel, furniture, and transportation equipment. It is not clear, though, what sectoral characteristics explain these differences.

Different explanations, sometimes contradictory, are advanced. The tenet of the technology argument suggests that the observed differences in survival rates across industries are due to varying innovative environments [Audretsch (1995)]. However, studies of industries at comparable levels of technology report unequal hazard rates. For example, Japanese pharmaceuticals resist more than the electrical machinery sector to the impact of the business cycle, although both are high-tech industries [Watanabe*, et al.* (2003)]. In Germany, Mata*, et al.* (1995) find that the probability of survival across industries is not particularly sensitive to the stage of the business cycle.

Although credit is not thought to be an important determinant of survival in developed economies, Asea and Blomberg (1998) find that banks in the USA adopt a more lax lending behaviour during periods of booms but tighten credit allocation in periods of recession. This change in bank behaviour may help explain the increase in firm exit in the USA when the economy is in recession. Another explanation is that in a growing sector, price-cost margins may be higher than normal. As a result, even firms smaller than the MES may operate without risking ejection from the industry [Audretsch and Mahmood (1995)] leading to higher survival rates. However, these firms tend to exit when the economy starts declining.

In summary, it is difficult to propose stylised facts about the sectoral determinants of firm survival. What is undisputable is that the rates of survival vary across industries.

2.2.5. Location and Firm Survival

Firms in different locations may also record different rates of survival. As McPherson (1995: 34) notes, this may be due to 'differences in demand conditions, degree of competition, or ability to procure inputs.' For instance, Reynolds (1938) and Klepper and Simons (2000) discuss the concentration of the American tyre industry in Akron, Ohio. They find that tyre firms located near Akron have 40 percent higher survival rates than firms located elsewhere. They explain that this owes to access to skilled labour and machinery thanks to the cluster effect.

Another reason may be asymmetric shocks given that most economies are characterised by regional specialisations. In Kenya, Mombasa has the distinctive characteristic of a coastal economy driven by tourism. Hence, a shock affecting the tourism industry would probably have a larger impact on firms in Mombasa than in the rest of the country. In an African context, Mead and Liedholm (1998) and McPherson (1995) have found that location is an important determinant of firm survival.

3. Discussion of Variables and the Data

We start with a discussion of the variables used in the empirical part followed by a note on the limitations of the data and the descriptive statistics.

3.1. Discussion of the Variables

The construction of the dependent variables for both the dichotomous survival models and the hazard model is explained in Section 4. The loan variable measures whether a firm had used a loan up to a specific year between 1992 and 1999.[3] It takes value 1 if a firm used a bank loan and zero otherwise. The overdraft variable proxies for a firms' opportunity to use a more accessible form of finance when faced with short-term cash flow problems. The size variable used is the log of a firm's number of full time workers. The choice of this variable is standard practice in the literature on developing economies. The variable is relatively easy to count and it does not need to be deflated unlike alternative measures.

The ethnicity dummy variable captures the ethnic background of the owner. We distinguish between Kenyans of African origin, those from Asian descent (we call them Kenyans of Indian origin as Kenyans of Asian descent originated principally from India) and Others. This latter group is made up of non-Kenyans, Kenyans of Middle Eastern origin and a few observations we could not place in either of the first two groups. This distinction attempts to capture the dominant role of Kenyans of Indian origin in the manufacturing sector [see Nkurunziza (2004) for details]. Regional and sectoral dummies are also included in the light of the discussion in the previous section.

3.2. A Note on Data Limitations

It could be argued that the lack of specific information on firm dissolutions may overstate the probability of firm failure when we assume that all firms 'exiting' the sample have died. If a firm observed in 1992 is not in the 1999 sample, it does not necessarily mean that it has

[3] See Nkurunziza (2005a) for details on the construction of the variable and a detailed discussion of other explanatory variables.

closed down. Some firms may have moved places and become hard to locate. Some others may have refused to be re-interviewed although these cases are rather rare in our sample.

The extent of the potential bias is not serious for the following reason. Information in Table 3.2 of Nkurunziza (2004) shows that 13.4 percent of the firms interviewed in 1992 were 'lost' in 1993. The fact that firms could not be located just one year after the previous interview suggests that they had exited. The rate of attrition in the period 1993-1994 is comparable at 12.6 percent and the yearly attrition rate between 1994 and 1999 is even lower at 11.4 percent.

This constancy in the rate of attrition suggests that it may be considered a genuine exit rate produced by a normal creative destruction process. A binomial probability test of the null that the three attrition rates are not statistically different is used to support this hypothesis.[4]

4. Modelling Firm Failure as a Dichotomous Process

In the first sub-section, we construct three dependent variables used to estimate probit models of firm failure. Similar definitions of firm failure have been used in studies by Audretsch (1991), Evans (1987a); Evans (1987b); Nafziger and Terrell (1996); and Ong (2001). The second sub-section presents the descriptive statistics while the last sub-section discusses the empirical results.

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[4] See StataCorp (2003a) for a brief discussion of the binomial probability test. We first generate three variables by giving a value of zero to all firms that exit from one period to the next and value one to those remaining. The probability of survival or picking a value of one is 0.866, 0.874 and 0.886 for the three respective transition periods, i.e. 1992 to 1993; 1993 to 1994 and 1994 to 1999. Proving that these exit rates are statistically equal is equivalent to showing that the first two probabilities of success are not statistically different from the third. Setting the assumed rate of success to 0.886 in the period 1992-1993 and using a binomial probability test returns a $p-value = 0.40$ so we cannot reject the null that the rates of success between 1992-1993 and 1994-1999 are not statistically different. A similar test for 1993-1994 returns a $p-value = 0.29$ so we cannot reject the null that the two rates are identical. We conclude that the yearly rates of attrition between 1992 and 1999 are not statistically different so they represent genuine exit rates.

4.1. Probit Models of Firm Failure

Assume that f_i is a state variable representing a firm in either of two states: $f_i = 1$ if a firm i exits and $f_i = 0$ if a firm is in operation. The first discrete variable, called *'Exit'*, is defined as the probability that a firm observed in 1992 is no more under observation in 1999 meaning it has failed between 1992 and 1999. The *Exit* variable takes value 1 if a firm has failed and zero otherwise. Hence exit at any time in the period 1992-1999 is given by:

$$\begin{cases} Exit = 0 \ \ if \ \ [f_i(1999) = 0 \,|\, f_i(1992) = 0] \\ Exit = 1 \ \ otherwise \end{cases} \tag{1}$$

where 1992 and 1999 represent the beginning and the end of the observation period, respectively. Based on this definition, Table 2 shows descriptive statistics on exit rates of small and large firms between 1992 and 1999.

Table 1. Exit Rates of Small and Large Firms

	1992	1999	*Exits*	*Exits as % of* 1992	*Yearly exit rate*
$Size \leq 30$	136	40	96	71	10%
$Size > 30$	88	32	56	64	9%
Total	224	72	152	68	10%

These figures suggest only a marginal difference between exit rates of small and large firms. The lack of a strong correlation between firm size and the rates of exit may be due to the way size groups are defined. In chapter 6 of Nkurunziza (2004) where firm size and exit are investigated further, defining size groups as quartiles appears to show some negative correlation between size and exit.

The second discrete variable, called *'Death'* takes value 1 in the immediate year following a firm failure and zero in the years before. For example, a firm that is in the sample in 1992 and 1993 has zero values for those two years but takes value 1 in 1994.

$$Death_{it} = 1 \; if \; \begin{cases} f_{i(t+\tau)} = 1 \\ f_{it} = 0 \end{cases} \tag{2}$$

where τ is the time unit, a year in our case.

The third dependent variable is called *'Lastyear'*. As its name indicates, it takes value 1 in the last year it was observed and zero otherwise. Hence a firm observed between 1992 and 1994 takes value 1 in 1994 and zero in 1992 and 1993. *'Lastyear'*, is constructed as:

$$Lastyear_{it} = 1 \; if \begin{cases} f_{it} = 1 \\ f_{i(t-\tau)} = 0 \end{cases} \tag{3}$$

The difference between '*Exit'* and the last two variables is that the latter attempt to 'date' the year of failure whereas the former just considers the occurrence of firm failure. Variables defined in equations (2) and (3) are used in the hazard models estimated in Section 5. On the basis of the discussion in Section 2, the estimating equation is:

$$\Pr\left(failure = 1 \middle| C, S, A, K, I, R \right) = F\left(C, S, A, K, I, R \right) \tag{4}$$

Where C, S, A, K, I, R are credit use, size, age, ethnic background, industrial dummies, and regional dummies, respectively. Technology is not included in the analysis due to the lack of appropriate data.

4.2. Descriptive Statistics

The descriptive statistics refer to the full sample and to 1992. The first three variables in the table are discussed in Section 4.1. The other variables are discussed in Section 3.1.

Table 2: Descriptive Statistics

	Full Sample			1992 Sample		
	Mean	**Std. Dev.**	**# Observ.**	**Mean**	**Std. Dev.**	**# Observ.**
Exit	0.571	0.495	662	0.683	0.466	224
Last year	0.226	0.419	662	0.133	0.341	224
Death	0.261	0.439	896	0	0	0
Lag overdraft use	0.604	0.489	584	0.628	0.484	223
Lag loan use	0.251	0.434	497	0.141	0.349	206
Log of size	2.839	1.667	662	2.845	1.825	224
Log of age	2.727	0.788	662	2.585	0.904	224
Kenyan African	0.427	0.495	662	0.420	0.495	224
Kenyan Indian	0.508	0.500	662	0.504	0.501	224
Other Ethnicity	0.070	0.255	662	0.080	0.272	224
Textiles sector	0.238	0.426	662	0.250	0.434	224
Food sector	0.218	0.413	662	0.228	0.420	224
Metal sector	0.263	0.441	662	0.259	0.439	224
Wood sector	0.281	0.450	662	0.263	0.441	224
Mombasa region	0.173	0.379	662	0.174	0.380	224
Nakuru region	0.092	0.289	662	0.094	0.292	224
Eldoret region	0.092	0.289	662	0.089	0.286	224
Nairobi region	0.643	0.479	662	0.643	0.480	224

Note: Values are lagged only in the full sample.

4.3. Empirical Results

Table 3 reports econometric results of the models of firm exit following the definition in equation (1). The first column estimates a model that restricts the sample to 1992. The second column estimates the 'Exit' model using the full sample with lagged credit variables. Lagging the credit variables captures the fact that credit influences firm exit in the next period.

Table 3: Probit Models of Firm Exit over the Period 1992-1999
Dependent variable is 'Exit' as defined in equation (1)

	Exit in 1992	**Exit Full**
Lag of overdraft use	-0.584**	-0.168
	[0.292]	[0.232]
Lag of loan use	0.849***	0.654***
	[0.302]	[0.204]
Ln of size	-0.053	-0.095
	[0.078]	[0.064]
Ln of age	-0.150	-0.222*
	[0.128]	[0.121]
Kenyan of African origin	-0.250	-0.103
	[0.279]	[0.219]
Other Ethnicity	1.063**	1.087**
	[0.435]	[0.452]
Textiles sector	-0.614**	-0.873***
	[0.275]	[0.196]
Food sector	-0.479*	-0.502**
	[0.290]	[0.225]
Metal sector	-0.448	-0.452**
	[0.281]	[0.198]
Mombasa region	0.405	0.597***
	[0.292]	[0.218]
Nakuru region	0.241	-0.003
	[0.368]	[0.277]
Eldoret region	-0.308	-0.234
	[0.331]	[0.267]
Constant	1.639***	-0.238
	[0.500]	[0.534]
Log Pseudo-likelihood	-114.536	-223.249
Pseudo R-squared	0.111	0.236
$\chi^2(.)$	26.91***	70.25***
Observations	205	372

Bracketed numbers are White (1980) robust standard errors. 3, 2, and 1 star, correspond to 1, 5 and 10 percent significance level, respectively. The reference groups are Wood, Nairobi and Kenyan of Indian origin for sector, region and ethnicity, respectively. Variables are not lagged in the 1992 model. Time dummies for 1993 and 1994, not reported, are positive and highly significant in the second model.

Both models show that the loan variable is significant and positive, implying that loans precipitate firm failure. In the 1992 model, the negative sign and significance of the overdraft coefficient suggests that overdraft helps firms to resist. The discussion that follows is based on Model 2 which displays the best fit and covers the full sample period.

Credit and Firm Survival: The loan variable is positive and highly significant suggesting that past loans precipitate firm exit. The negative sign of the overdraft variable suggests that access to this facility increases firm survival but the effect is not statistically significant. Considering that the coefficient on loans measures the impact on the probability of failure of a discrete change from not having used a loan to having one, the effect of credit on firm resilience is given by the increase in the odds of firm failure due to loans. Other things being equal, the odds of firm failure are $e^{0.654} \approx 1.923$ times higher for firms using loans than for firms that do not use them. That is, the odds of failure increase by about 92 percent when firms use loans.

Control Variables: The size variable is negative but only significant at 14 percent probability level. The implication is that size does have an effect on firm resilience, which contradicts the literature finding that larger firms have lower hazards. The finding in McPherson (1995) study of four countries in Southern Africa is similar to ours. In his results, size is positively related to survival in only one out of four countries, as we have discussed in Section 2.2.1. Nafziger and Terrell (1996) study on India also finds that size has no statistically significant effect on firm survival. Moreover, using data on US manufacturing, Audretsch and Mahmood (1995) find that size increases survival when firms are relatively young but has no significant impact when they have survived for 8 years. Therefore, although studies have found a positive relationship between size and survival [see Evans (1987b); Harding*, et al.* (2004); Ong (2001); Audretsch (1995); Klepper (2002)], the result does not seem to be robust across studies. More empirical analyses using African data are necessary to clarify this relationship.

Age is significant with a negative sign confirming the theoretical prediction that older firms resist better. With respect to ethnicity, the finding in Table 5.3 does not suggest that there is a difference in survival of firms owned by Kenyans of African origin and those owned by Kenyans of Indian origin. However, the positive sign and significance of the variable 'Other Ethnicity' suggests that firms in this group, mainly owned by Europeans and other non-Kenyans, had high rates of failure. This may reflect the fact that faced with a major crisis foreign firm owners had the option to close down their businesses and leave the country to try their luck elsewhere.

All sectoral variables are negative and significant. The meaning is that relative to the wood sector, all the other three sectors have higher rates of survival. The poor resilience of firms in the wood sector relative to all the other three may have been partly due to the government's tightening of environmental laws. New laws on logging were introduced in the early 1990s, affecting negatively the supply of plywood. The high hazard of firms in Mombasa may be associated with the level of political violence in the 1990s that affected particularly the tourism industry, the backbone of economic activities in Mombasa.

Are the results discussed in this section robust to different estimation methods? The next section uses more sophisticated models of firm survival or hazard models to test for the effect of credit on survival. The difference between the results in section 4 and those in section 5 below is that while the former restricts modelling to the event of firm failure, section 5 models both the event of failure and the time it takes a firm to fail. In a comparison of Logit, OLS, and hazard models, Allison (1982) shows that hazard models fit best event history data.

5. Modelling Failure Using Hazard Models

We briefly discuss the theoretical aspects of hazard models in the first sub-section. The second sub-section presents and discusses the empirical results.

5.1. Theoretical Discussion

Despite the rich theoretical econometric literature on survival models [see Wooldridge (2002); StataCorp (2003a)] empirical literature on survival analysis using African data is rather scant.[5] We describe the methodology underlying survival analysis and apply it to about 220 firms originally surveyed in 1992 and resurveyed in 1993, 1994 and 1999.

In practice, duration is conveniently modelled as a hazard function. Therefore, to ensure that the empirical results from different models are easily compared, we model the hazard of firm failure rather than survival.[6] We estimate a hazard rate measuring the rate at which firm failure occurs. Equivalently, it is the rate at which a firm survives the hazard of exit in a specific year given firm characteristics. The hazard model shows the impact of a covariate on the rate of exiting the sample at time $t+h$ conditional on having operated until time T, the duration variable. A general formulation of a continuous hazard function may be written as [see Wooldridge (2002)]:

$$\lambda\left[t;X\left(t\right)\right]=\lim_{h\to 0}\frac{\Pr\left[t\leq T<t+h\middle|T\geq t,X\left(t+h\right)\right]}{h} \tag{5}$$

where $\lambda\left(t\right)$ is the hazard rate and X is the same vector of explanatory variables given in equation (4). For $h>0$, the term $P\left[t\leq T<t+h\middle|T\geq t,X\left(t+h\right)\right]$ is the probability that a

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[5] McPherson (1995) claims to be the first author to have used a hazard model examining firm survival both in developed and developing countries.

[6] We use the terms survival and failure interchangeably, keeping in mind that one is the flip side of the other.

firm fails in the interval $[t, t+h)$ given that it has survived up to time t. Modelling duration raises a number of issues that are discussed in the rest of this section. The first issue is right censoring. All the firms enter in the sample in the same year 1992 and those that have not failed by 1999 are censored.[7] Because durations differ across firms we have:

$$dur_i = \min\left(t_i, c_i\right) \tag{6}$$

where t_i is firm $i's$ length of time until exit and c_i is the firm's censoring time. To address the issue of right censoring, hazard models use two dependent variables. The first is the duration variable *'Dur'* and the second is the dummy variable capturing the occurrence of the hazard, constructed in equation (3). The empirical duration variable is:

$$\begin{aligned}
&dur = 1 \; if \; f_i(1992) = 0 \\
&dur = 2 \; if \; f_i(1992) = 0 \; and \; f_i(1993) = 0 \\
&dur = 3 \; if \; f_i(1992) = 0 \; and \; f_i(1993) = 0 \; and \; f_i(1994) = 0 \\
&dur = 8 \; if \; f_i(1992) = 0 \; and \; f_i(1993) = 0 \; and \; f_i(1994) = 0 \; and \; f_i(1999) = 0
\end{aligned} \tag{7}$$

The second issue relates to the shape of the hazard function. As our interest is to determine how different firm characteristics affect the hazard rate, we need to parameterise equation (5) and analyse its parameters. We follow general practice and estimate hazard models with multiplicative covariates of the form:

$$\lambda\left(t_j\right) = \lambda_0\left(t\right) g\left(X_j\right) \tag{8}$$

where $\lambda_0\left(t\right) > 0$ is the 'baseline hazard' common to all observations in the population of firms. Individual hazard functions differ proportionately to covariates according to the function $g\left(X_j\right)$. Typically, $g\left(X_j\right)$ is parameterised as an exponential function:

$$g\left(X_j\right) = \exp\left(X_j \beta\right) \tag{9}$$

[7] Left censoring is also possible when firms enter in the sample at different dates. Left censoring does not apply to our data as we restrict the sample to the 224 firms that were surveyed in 1992.

where β is the vector of regression coefficients. Parametric estimation of the hazard model depends on the functional forms assumed for $\lambda_0(t)$. If one is just interested in how the covariates shift the hazard function without having to determine the baseline hazard, it is appropriate to estimate a Cox proportional hazard (CPH) model. However, if one wants to know the shape of the baseline hazard, parametric models must be estimated by assigning a distribution to the baseline hazard. We assume three different distributions for the baseline hazard, namely the exponential, Gompertz and Weibull functions.

5.1.1: The Cox Proportional Hazard (CPH) Model

CPH model is the most popular of all hazard models thanks to its advantages over parametric models. First, it assumes time dependence without having to specify time's functional form. Second, CPH has the advantage of accommodating stratified models without needing to specify the interaction of the variables with time. As its name indicates, the CPH model assumes that the hazard rate changes proportionately with respect to time. For instance, if the hazard of failure of a firm using credit is two relative to a firm without access to credit, this hazard rate remains the same whether firms are observed for one, two, three, or eight years. Third, the main motivation behind the popularity of CPH model is that it does not require specification of the form of the baseline hazard. Equation (8) is readily estimated as a CPH whenever the functional form of $\lambda_0(t)$ is unspecified.

The model allows a straightforward determination of the impact of each covariate on the hazard function if the latter is assumed to be of the form specified in equation (8). When is the CPH model appropriate? Whether or not the proportionate hazard assumption is valid in a specific application must be tested. Both global and covariate-level tests are available to show how the assumption fits empirical data. Some authors recommend using alternative models if the CPH assumption is rejected but Allison (1984) argues that the flexibility and the generality of the CPH model justify its use even when the proportionality assumption is violated.

A limitation of the model is that it is meant to fit flow (continuous) rather than grouped data (discrete). Although many applications of the CPH model in the social sciences assume flow data, continuous durations are rather rare, strictly speaking. Even when underlying economic phenomena are continuous, they are measured as discrete events. For instance, unemployment is usually measured in months or weeks. Our own measure of survival is measured in years. The consequence is that there are firms with identical durations, a problem that may affect the precision of the results of the CPH model.

Specific optimisation algorithms have been developed to address the problem of identical durations. The two methods that we use derive approximations of exact marginal log-likelihood by maximising appropriate partial log-likelihood functions that take into account the presence of ties in the data.[8] These methods are the Peto-Breslow and Efron approximations [see StataCorp (2003b)]. The former provides a faster approximation while the latter is slower but gives a more precise approximation.

5.1.2: Parametric Model with a Constant Hazard Rate

When the hazard rate is assumed to be constant, an exponential functional form is used for the baseline hazard. This assumption implies that the log of the survival function is linearly related to time. In this case, the baseline hazard is $\lambda_0(t) = 1$, which is a special case of the

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[8] These are called partial log-likelihood because likelihood functions are constructed only for the uncensored observations.

Weibull function with an ancillary parameter $p=1$ (see below). Indeed, exponential and Weibull are nested models.

5.1.3: Parametric Models with Monotonic Hazard Rates

Weibull and Gompertz parametric forms fit the data where the hazard rate is assumed to change monotonically, either increasingly or decreasingly. In Weibull case the log of the hazard increases or decreases with the log of time. The Gompertz functional form fits the data where the log of the hazard increases or decreases linearly with time. In these models, the baseline hazard is equal to:

$$\lambda_0(t) = p * t^{p-1} \tag{10}$$

where p is the function's shape or ancillary parameter. If $p>1$ the hazard of firm failure increases over time. Such a hazard function is called positive time dependent. Negative time dependency obtains when the hazard declines with time, meaning that $p<1$.[9]

It is not clear which one of the three parametric models to use in empirical applications. In theory, the most decisive information needed to choose which model to estimate is the way time relates to the log of the hazard. In practice, this is difficult. Knowing whether the relationship is linear or exponential is not easy. This problem has led some authors to conclude that the appropriate parametric model should be used if only one is sure how time should enter the equation. Otherwise, it is advisable to stick to the Cox model. Allison (1984) suggests that one should estimate an exponential model and compare it with one of the two alternatives. Based on the log-likelihood statistic, the model with the best fit

[9] The notion of time dependency is especially important in labour markets where one is interested in the probability that an unemployed finds employment given how long he has been jobless.

is retained. If the exponential model has a significantly higher log-likelihood, drop the other model and re-estimate and compare with the alternative model.

5.1.4. The Hazard Model and Unobserved Heterogeneity

As in panel data models, survival models are prone to the problems of unobserved heterogeneity, also called 'frailty'. This is the case when the hazards of different categories of firms have different distributions. Including independent explanatory variables is an attempt to reduce the effect of heterogeneity. However, it is reasonable to acknowledge that there may still be omitted variables that affect a firm's survival rate. These may include the level of human capital, changes in input and output prices, etc. Hazard models are not amenable to specifications that are similar to fixed effects and other instrumental variable estimation techniques discussed in Nkurunziza (2005a). There may be, therefore, some residual heterogeneity that hazard models cannot control for.

In this light, three general assumptions are adopted with respect to heterogeneity in hazard models [Wooldridge (2002: 703)]. Firstly, heterogeneity is independent of the observed covariates, the starting times and the censoring times. With this assumption, frailty introduces no bias but accounting for its presence when it is significant increases efficiency gain, leading to better inference. The second assumption is that the distribution of heterogeneity is known up to a finite number of parameters. The third assumption is that heterogeneity enters the hazard function multiplicatively. Hence, introducing heterogeneity in equation (8) and given equation (9) we have:

$$\lambda\left(t_j;X_j,\nu_j\right)=\lambda_0\left(t\right)\nu_j\exp\left(X_j\beta\right) \tag{11}$$

where $\nu_j > 0$ is unobserved heterogeneity with mean one and variance θ. Multiplicative frailty is convenient because if $\alpha_j = \log\left(\nu_j\right)$, equation (11) can be conveniently estimated in the form:

$$\lambda\left(t_j; X_j, \alpha_j\right) = \lambda_0\left(t\right)\exp\left(X_j\beta + \alpha_j\right) \tag{12}$$

In this formulation, the log-frailties α_j are interpreted like random effects in linear models. For computational convenience, empirical estimations usually assume frailty to have a Gamma or an inverse-Gaussian distribution. It should be noted that frailty occurs either at the observation or at group level. Finally, the variance of the frailties θ and a likelihood ratio test of the null that the variance of the frailty is zero are used to test whether heterogeneity is statistically significant [see StataCorp (2003b)].

The fact that our sample period has a gap between 1994 and 1999 may slow the maximisation of the partial likelihood function but it does not pose fundamental econometric problems. In survival analysis, multiple-record data are allowed to have gaps [see StataCorp (2003b: 292)].

5.2. Hazard Models: Empirical Results

First, we test for the CPH assumption in Table 4 and present the econometric results of the CPH model in Table 5 and those of parametric models in Table 7.

Table 4: Test of the Proportional Hazard Assumption

	Parameters	$\rho - test$
Lag of overdraft use	-0.297	0.074
	[0.225]	[0.588]
Lag of loan use	0.516***	-0.202
	[0.183]	[0.135]
Ln of size	-0.095	0.108
	[0.070]	[0.424]
Ln of age	-0.196*	-0.040
	[0.110]	[0.781]
Kenyan of African origin	-0.225	-0.004
	[0.206]	[0.980]
Other Ethnicity	-0.726	0.078
	[0.575]	[0.536]
Textiles sector	-0.275	-0.294**
	[0.207]	[0.017]
Food sector	-0.291	-0.122
	[0.216]	[0.367]
Metal sector	-0.315**	0.054
	[0.157]	[0.746]
Mombasa region	0.084	0.201
	[0.167]	[0.151]
Nakuru region	0.160	-0.021
	[0.279]	[0.873]
Eldoret region	-0.309	0.095
	[0.328]	[0.419]
χ^2 Global test		9.64
		[0.647]
Log Pseudo-Likelihood	-486.557	
Wald statistic	29.08***	
Observations	372	

Bracketed numbers are White (1980) robust standard errors for the parameters and robust *p-values* for the test column. Reference groups are Kenyan of Indian origin, Wood and Nairobi for ethnicity, industry and region, respectively. The parameters are calibrated as model coefficients not hazard ratios. 3, 2 and 1 stars mean that the statistic is significant at 1, 5 and 10 percent significance level.

Covariate-level r - *test* is a test of the null that the covariate has the same proportional impact on the hazard everywhere along the hazard function. For instance the hazard ratio of failure for firms using loans and those not using loans remains the same over time because the test does not reject the null. If the null is rejected, as is the case for the textiles dummy, it means that the hazard ratio in the textiles relative to firms in other sectors is not constant over time. The global test has the same interpretation but relates to the equation as a whole.

The global test confirms that the CPH assumption is satisfied. At covariate level all the variables but the textiles dummy, satisfy the condition. A separate log-rank test of the equality of survivor functions of the textiles dummy returns a *p-value* of 0.843, implying that firms in the textiles sector do not have, after all, a survivor function statistically different from that of firms in other sectors. We, therefore, proceed to estimate Cox hazard models.

Table 5: CPH Models with Alternative Methods of Treating Ties
Dependent variables are 'lastyear' and duration (Dur)

	Breslow Method for Ties		Efron Method for Ties	
	No Frailty	**Frailty**	**No Frailty**	**Frailty**
Lag of overdraft use	-0.297	-0.297	-0.358	-0.358
	[0.225]	[0.347]	[0.327]	[0.369]
Lag of loan use	0.516***	0.516*	0.650***	0.650**
	[0.183]	[0.267]	[0.243]	[0.271]
Lag of Log of size	-0.095	-0.095	-0.114	-0.114
	[0.070]	[0.098]	[0.095]	[0.100]
Log of age	-0.196*	-0.196	-0.280*	-0.280
	[0.110]	[0.173]	[0.152]	[0.179]
Kenyan-African	-0.226	-0.226	-0.270	-0.270
	[0.206]	[0.324]	[0.284]	[0.334]
Other Ethnicity	-0.726	-0.726	-1.081	-1.081
	[0.575]	[0.740]	[0.803]	[0.754]
Textiles sector	-0.275	-0.275	-0.517*	-0.517*
	[0.207]	[0.281]	[0.267]	[0.282]
Food sector	-0.291	-0.291	-0.512*	-0.512*
	[0.216]	[0.304]	[0.288]	[0.308]
Metal sector	-0.315**	-0.315	-0.454**	-0.454*
	[0.157]	[0.269]	[0.223]	[0.271]
Mombasa region	0.084	0.084	0.248	0.248
	[0.167]	[0.278]	[0.227]	[0.281]
Nakuru region	0.160	0.160	0.165	0.165
	[0.279]	[0.370]	[0.377]	[0.369]
Eldoret region	-0.309	-0.309	-0.445	-0.445
	[0.329]	[0.410]	[0.435]	[0.412]
$\theta - frailty$		1.13e-07		1.13e-07
[ ]= std. error		[4.70e-07]		[0.000]
$\bar{\chi}^2(1)\ for\ \theta = 0$		9.4e-06		1.3e-05
		[0.499]		[0.499]
Log Pseudo-Likelihood	-486.557	-486.557	-450.98	-450.979
Wald statistic	29.08***	10.99	37.36***	22.09**
Observations	372	372	372	372

Numbers in brackets are White (1980) robust standard errors. The reference groups for dummies are Kenyan of Indian origin, wood and Nairobi for ethnicity, industry and location. The parameters are model coefficients not hazard ratios. 3, 2 and 1 stars mean that the statistic is significant at 1, 5 and 10 percent significance level, respectively. The bracketed value below the chi-squared figure for frailty=0 is a *p-value*.

Breslow and Efron methods are used to account for the existence of ties in the data. Moreover, the models assuming Gamma distributed frailty are compared with those that do not assume frailty. The $\overline{\chi}^2$ test of frailty fails to reject the null that the frailty coefficient is zero.[10] The non-significance of frailty is probably the reason why models assuming frailty and those not assuming it have the same coefficients but different standard errors. The model based on Efron's approximation is better than the one using Breslow method since it has a higher log pseudo-likelihood statistic. We, therefore, base our brief discussion on the model using Efron's approximation.

Table 5 confirms the results of the probit model in Table 3. The overdraft variable is negative but non-significant whereas the loan variable is positive and highly significant. Using loans increases the hazard ratio of failure by $100\left(e^{0.650}-1\right)\approx 92\%$, on average, relative to firms not using loans. This figure is exactly the same as the one found from the probit model. This finding contrasts with the literature on developed economies where credit is not considered as a relevant determinant of firm survival.

Size seems to have a beneficial effect in view of its negative coefficient but, as in the probit model, it is not significant. As noted earlier, the study by McPherson (1995) found a similar result. This study offers a particularly appropriate comparison as it also controls for credit using African data and a CPH model. Age is negative and significant, supporting the expected effect that firms' resilience increases with their age. This confirms the literature surveyed in Section 2 but the result regarding size does not seem to support the claim by Audretsch and Mahmood (1995) and Geroski (1995) that the positive relationship between

[10] $\overline{\chi}^2$ is different from the usual χ_1^2; it is a fifty-fifty combination of χ_0^2 (point mass at zero) and a χ_1^2; see StataCorp (2003b) for details.

size, age and firm survival is one of the most striking stylised facts arising from empirical research on industry dynamics.

With the hazard model, we are able to show the extent to which different groups of variables affect the hazard of firm failure in every period. Table 5.6 summarises this information.

Table 6: Survivor Probabilities Adjusted for Groups of Variables

Years	No Adjust	No Overd.	No Loan	No Overd. & Loan	No Size	No Age	No Ethnicity	No Industry	No Region
1993	0.866 [0.023]	0.845	0.869	0.843	0.851	0.848	0.869	0.865	0.867
1994	0.759 [0.029]	0.735	0.784	0.747	0.304	0.728	0.764	0.757	0.761
1999	0.330 [0.031]	0.281	0.350	0.291	0.304	0.278	0.337	0.326	0.331

Values in brackets are standard errors

The statistics in the Table are read as follows. On average, the probability of firm survival given all the variables discussed in the previous models was about 0.87 in 1993 and 0.33 in 1999. For firms that did not use overdrafts but which had all the other characteristics of the sampled firms, survival was 0.84 in 1993 and 0.28 in 1999. These probabilities are lower than those from the baseline probabilities in column 1. On the other hand, firms that had not used credit by 1993 had almost the same survival probabilities as those using loans, given all other characteristics. However, survival in 1994 is highest for firms not using loans, another suggestion that the problem associated with the use of loans emerged after 1993 (see discussions in Nkurunziza (2004)).

To complete the analysis, we estimate hazard models which do not assume the proportional hazard assumption. We estimate three models that use different assumptions on the distribution of the baseline hazard. These are the Exponential, Gompertz and Weibull models.

Table 7: Parametric Models of Firm Resilience

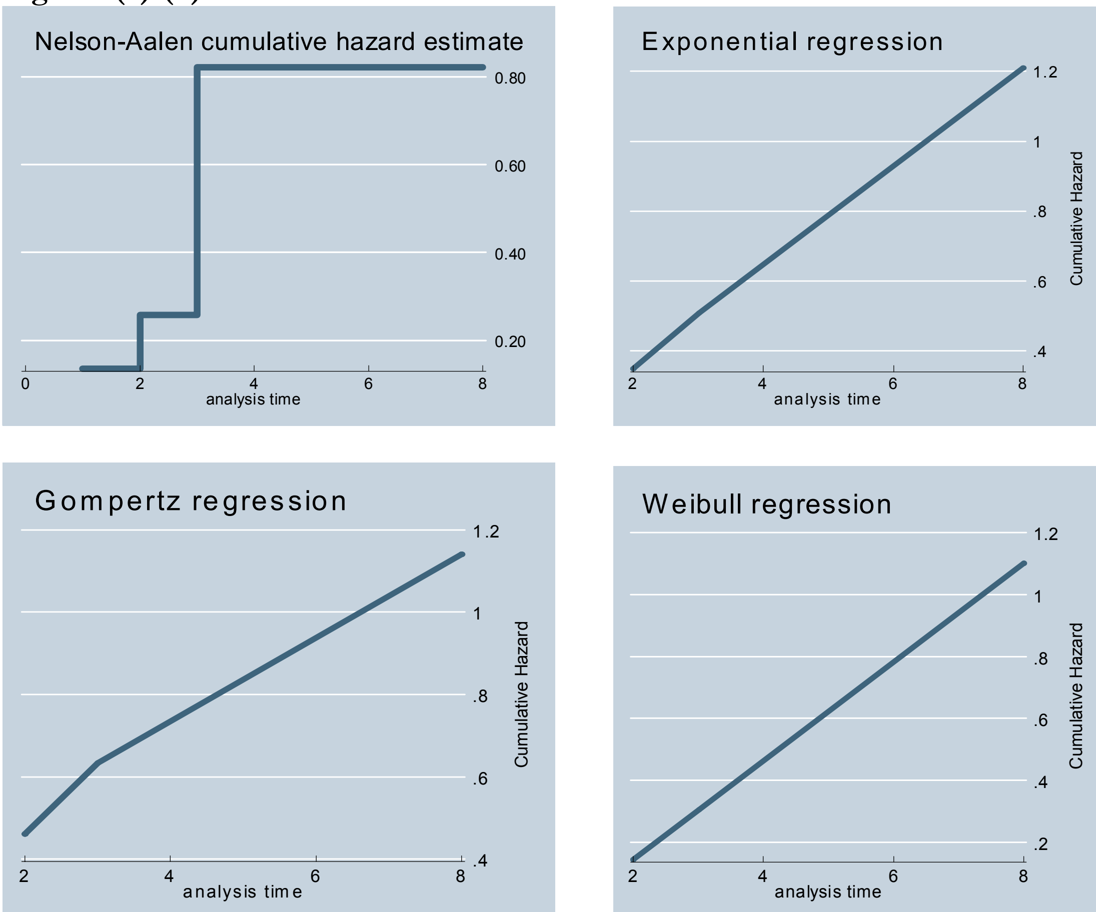
Dependent variables are duration (Dur) and Lastyear

	Exponential Models		Gompertz Models		Weibull Models	
	No Frailty	Frailty	No Frailty	Frailty	No Frailty	Frailty
Lag overdraft use	-0.269	-0.313	-0.348	-0.348	-0.252	-0.503
	[0.378]	[0.370]	[0.341]	[0.323]	[0.390]	[0.496]
Lag loan use	0.550**	0.610*	0.655***	0.655**	0.528*	0.886**
	[0.267]	[0.331]	[0.240]	[0.262]	[0.274]	[0.426]
Log of size	-0.075	-0.078	-0.075	-0.075	-0.076	-0.112
	[0.105]	[0.104]	[0.094]	[0.098]	[0.107]	[0.148]
Log of age	-0.695***	-0.693***	-0.524***	-0.524***	-0.731***	-1.071***
	[0.138]	[0.176]	[0.139]	[0.178]	[0.164]	[0.384]
Kenyan Afr.	-0.477	-0.497	-0.409	-0.409	-0.490	-0.793
	[0.329]	[0.339]	[0.297]	[0.317]	[0.337]	[0.511]
Other Ethnic	-1.465	-1.490*	-1.260	-1.260*	-1.503	-2.167*
	[0.913]	[0.785]	[0.844]	[0.752]	[0.932]	[1.157]
Textiles	-0.727***	-0.748**	-0.645**	-0.645**	-0.742**	-1.096**
	[0.278]	[0.304]	[0.257]	[0.283]	[0.291]	[0.502]
Food	-0.775**	-0.789**	-0.687**	-0.687**	-0.790**	-1.164**
	[0.314]	[0.325]	[0.288]	[0.306]	[0.322]	[0.547]
Metal	-0.451*	-0.473	-0.430*	-0.429	-0.454*	-0.755
	[0.259]	[0.293]	[0.230]	[0.269]	[0.265]	[0.466]
Mombasa	0.289	0.306	0.258	0.258	0.295	0.489
	[0.250]	[0.302]	[0.225]	[0.279]	[0.256]	[0.465]
Nakuru	0.249	0.276	0.231	0.231	0.254	0.422
	[0.406]	[0.399]	[0.364]	[0.368]	[0.414]	[0.586]
Eldoret	-0.389	-0.377	-0.329	-0.329	-0.402	-0.445
	[0.472]	[0.426]	[0.432]	[0.409]	[0.483]	[0.590]
Constant	1.006**	1.080	0.959**	0.959	0.934*	1.773
	[0.503]	[0.710]	[0.463]	[0.623]	[0.493]	[1.425]
$\theta - frailty$		0.080		3.24e-07		2.501
Standard error		[0.279]		[2.02e-04]		[3.007]
$\bar{\chi}^2(1)\ for\ \theta = 0$		0.10		0.00		2.88**
		[0.378]		[1.000]		[0.045]
Shape Parameter			-0.154***	-0.154***	1.089***	1.840***
Standard error			[0.041]	[0.065]	[0.152]	[0.474]
Log Likelihood	-156.29	-155.985	-152.968	-152.968	-155.932	-154.490
$\chi^2(.)$	61.29***	34.91***	43.42***	29.98***	45.73***	36.60***
Observations	372	372	372	372	372	372

Bracketed numbers are White (1980) robust standard errors adjusted for clustering on firm. Reference groups for dummies are wood, Nairobi and Kenyan Indian for sector, region and ethnicity, respectively. The parameters are model coefficients not hazard ratios. 3, 2 and 1 stars mean that the statistic is significant at 1, 5 and 10 percent significance level, respectively. Frailty has an inverse Gaussian distribution.

Cumulated hazard functions derived from the three functions in Table 6 are shown in Figure 1 (a)-(d). The graphs are drawn from the equations with frailty when the latter is significant.

Figure 1(a)-(d): Cumulative Hazard Estimates



Nelson-Aalen plots the cumulative hazard over the sample period. The hazard is flat from year 3 onwards due to the gap between 1994 and 1999. The cumulative hazards of all three parametric models have the same shape and comparable values of cumulative hazards even if they are based on different assumptions.

The log likelihood statistics of the three models in Table 7 suggest that we focus on the Gompertz model for a brief discussion. As frailty is not significant in this model, we use the results without frailty. The variables of interest have the same signs as in the previous models, reinforcing previous results. The coefficient of the loan variable shows that the increase in the hazard of firm failure due to the use of loans is $100\left(e^{0.655}-1\right)\approx 92\%$, the same value obtained in the previous models. Age is negative and highly significant in all six models, confirming its importance for firm survival, as found earlier. However, consistent with the previous results, size is not significant although it keeps its negative sign.

This consistency in econometric results from different classes of models, especially the strong results on the loan variable, seems to support our central hypothesis that the use of loans led to the failure of many firms in the 1990s.

6. Conclusion

The motivation to study firm survival in Kenyan manufacturing in the 1990s is that, given the crisis that prevailed during the period, survival analysis is a necessary complement to the growth analysis of Nkurunziza (2005a). Results from a range of models confirm that past loans tended to precipitate firm failure and the magnitude of the negative impact of credit use on survival is similar across all the models. The odds of failure of firms using loans are 92 percent higher than for firms not using loans. The likely reason may be that firms that were indebted in the early 1990s became unable to pay their debts following the increase in interest rates and other macroeconomic shocks that occurred around 1993.

With respect to the other determinants of firm survival, age is found to increase firm survival, as other studies have suggested. However, size is systematically non-significant, a surprising result but which is not just particular to the present study. A similar finding has been reported by McPherson (1995); Mead and Liedholm (1998); Klepper and Simons (2000); and Gort and Klepper (1982).

The main contribution of this paper has been to show that the variables determining firm survival in shock-prone developing economies may be different from those identified in developed economies. The most important finding is that credit is a key explanatory factor of firm survival, a notable difference with the literature on developed economies where the variable is not an important determinant of firm survival. Moreover, of the two key variables explaining firm survival in developed economies, namely age and size, only age appears to be important in the Kenyan case. More studies on African manufacturing will be necessary to draw a definitive conclusion on the effect of size on survival of firms in Africa.

The analysis in this paper leaves some unanswered questions. First, what are the categories of firms that have the highest exit rates? Are they drawn from large, medium or small size groups? Second, what does the size distribution of firms look like in equilibrium? Third, how does the use of credit affect the size distribution? These questions are the subject of a follow-up paper.

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