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Determinants of firm sustainability in Estonia

Kadri Männasoo

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Abstract

This paper examines the determinants of firm sustainability in Estonia using discrete-time survival analysis with a complementary log-log hazard function. A firm is defined as sustainable if it meets the minimum capital requirement set by the law, and if it does not then it is described as being "distressed". The definition of "in default" stipulates that not only must the firm be short of the required capital, but it should also have exited or dropped out altogether. This study confirms the stylized fact that firms face higher risk during their start-up period. Firm distress and default hazard decrease over time, the latter however, non-monotonically being lagged relative to distress. At the industry level, manufacturing firms demonstrate a higher degree of robustness compared to trade and services companies. Most importantly, however, firm sustainability positively depends on efficiency, good stable asset return, low leverage and a large assets base.

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Author's e-mail address: kadri.mannasoo@epbe.ee

Non-technical summary

Determinants of firm sustainability help to explain corporate sector soundness on the aggregate level. This is an important component of the financial stability concept, where corporate sector soundness indicators also form part of the IMF on-going project on financial soundness indicators.

The empirical part of this study has been built up on survival analysis methodology. Survival analysis reveals the dynamic nature of the hazard or risk of firms becoming unsustainable over future periods conditional on having survived up to this particular period. Baseline hazard curves show the dynamics of hazard over the firm's lifetime. All firms that meet the minimum legal capital standards are defined as sustainable. Non-sustainable firms are divided into two sub-categories — firms in distress and firms in default. Distressed firms are those that fall short of the legally set minimum capital requirement. Firms in default not only fail in terms of being short of the required capital, but they also exit over the next period.

The underlying data is taken from the Estonian Commercial Register over the years 1994–2004. The sample only includes privately owned limited liability companies from the manufacturing, trade and services, construction and real estate industries, which are active in business and have had some kind of exposure to the financial sector (loan, leasing or issued debt) during their lifetime.

The trade and services sector as well as the construction industry turned out to be the most highly leveraged; however, a major part of their leverage is not debt, but rather related to everyday business transactions. Real estate firms on aggregate are the most exposed to credits from the financial sector. No clear pro-cyclical patterns of leverage can be read from the data. Although bank loans and long-term bank loans in particular show the strongest pro-cyclical co-movement, short-term liabilities such as payables to suppliers, accrued interests and other payments due gain in proportion during economic down-cycles.

The baseline survival curves revealed that both types of non-sustainability — distress and default — were time decreasing, the latter however, more in a non-monotonic manner. This confirms the stylized fact that firms are more vulnerable during the start-up period. When comparing industries, the manufacturing sector turned out to be the most robust in contrast to the most fragile, the trade and services industry. The estimated determinants significantly related to firm sustainability turned out to be assets size, leverage, volatility and rate of asset return as well as efficiency in terms of sales-to-total-costs ratio. While excessive leverage and high volatility of asset return increase the probability of a firm becoming non-sustainable, the remaining variables work in the opposite direction or improve the firm's outlook for survival. Interestingly, public limited companies are more prone to becoming distressed and eventually default. Obviously, the stricter regulations for public firms precipitate more frequent failures, and the higher capital costs for public firms are not set off against the option of raising market funds on a largely illiquid and thin domestic capital market.

Contents

1. Introduction

The issue of the soundness of a firm and the relationship between soundness and financial stability at the aggregate level are of continual interest for researchers and practitioners. Despite extensive literature no unanimous set of firm viability indicators has been defined. It is unlikely that a first-best selection of firm soundness indicators can be achieved given the heterogeneity of characteristics at firm, industry and country level.

In light of the numerous crises experienced in the 1990s, the IMF has been working on a proposed set of financial soundness indicators (Sundararajan et al. 2002; IMF FSI Compilation Guide, 2006), including a subset of corporate sector indicators. The macro-prudential analysis of the corporate sector; however, requires a broad range of data whilst the determinants of corporate vulnerabilities are rooted in different sources starting from micro-level factors such as firm financials and stock market data up to macroeconomic and structural factors. Being focused on similar issues, the aim of the present study is to explore the indicators of firm failure in the Estonian context. The annual, low frequency micro-data, however, does not lend itself to full-fledged macro-prudential analysis. The approach taken in this study is exploratory and carried out with the purpose of finding robust measures of firm sustainability. Hence, the present work has a somewhat different focus relative to studies predominantly aimed at predicting firm-level default or bankruptcy.

To the best knowledge of the author, the present study is the first attempt to model the probability of the failure of Estonian firms with the aim of identifying a robust set of firm sustainability determinants using survival analysis and discrete-time survival models in particular. In doing so, the present paper strives to merge two strands of literature: one dealing with firm failure (bankruptcy) at the micro level and the other focusing on corporate sector vulnerability from the financial stability perspective. The literature on bankruptcy mostly concentrates on firm-level implications and does not deal with the vulnerability issues at the sectoral level. The literature dealing with the soundness of the corporate sector; however, rarely makes use of firm-level data, being constrained by the availability of internationally comparable financial data, deficiencies of aggregation and small samples. The literature on firm demographics is placed somewhere in-between and mostly focuses on firm performance at industry level. The main interest in this line of research is related to firm entry and exit patterns, job flows and the viability of start-ups.

The few studies on firm demographics and survival dealing with transition economies (including Masso, Eamets and Philips, 2004 and 2006; Konings and Xavier, 2002) have not discovered any major transition specific anomalies, except the relatively low firm survival rates in the early years of economic transition. On the contrary, Konings and Xavier (2002) examine firm growth and survival in Slovenia over the turbulent transition period of 1994–1998 and provide evidence that is consistent with predictions for market economies. Their findings confirm the well-known stylized facts that the size, age and financial health of a firm can improve its prospects for survival and success.

The earliest and most-cited papers on predicting the failure of firms were written by Beaver (1966) and Altman (1968). Their work relied heavily on different financial ratios, with their properties thoroughly investigated. Beaver (1966) compared and evaluated 30 different financial ratios and concluded that six of them had superior performance in his profile analysis: (1) cash flow to total debt; (2) net income to total assets; (3) total debt to total assets; (4) working capital to total assets; (5) current ratio, and (6) no-credit interval.[1] However, he admitted the limitations of profile analysis, which relies on a simple mean comparison between failed and sound firms.

Altman (1968) proposed the well-known discriminant score model for predicting corporate bankruptcy. Discriminant analysis was performed on US manufacturing firms over the period 1946–1965. The resulting popular firm discriminant score or Z-score model suggests that an increase in working capital to assets ratio, retained earnings to assets ratio, profitability to assets ratio, market-to-book value ratio and sales-to-assets ratio does promote financial strength. The model has later been subject to numerous revisions. For instance, an adaptation for unlisted firms with the market-to-book value variable replaced with a book value equity-to-debt ratio. In 1977, Altman, Haldeman and Narayanan (Altman, 2000) constructed the second generation ZETA® credit risk model, which contained several enhancements compared to the original model. Instead of five variables seven were entered into the updated version: (1) return on assets; (2) stability of earnings measured using a normalized standard error; (3) interest coverage ratio; (4) retained earnings to total assets; (5) current ratio; (6) equity to total capital, and (7) log of total assets.

Künnapas (1999) has been investigating financial ratios for predicting the bankruptcy of Estonian manufacturing firms over 1996–1998. Like Altman (1968), he employs the discriminant analysis methodology. His proposed firm discriminant score (T-score) model for Estonian manufacturing corporations includes the net profit to total assets ratio, sales to assets ratio and current ratio, all having a positive impact on a manufacturing firm's financial strength.

The earliest study, which employs a parametric approach (a conditional

[1] Cash plus receivables (quick assets) minus current liabilities to operating expenses minus depreciation.

logit model) for predicting bankruptcy, was undertaken by Ohlson (1980). He made use of US firm data over the period 1970–1976 with a sample size of 105 subjects, 18 of them (17 percent) classified as firms in bankruptcy. Ohlson's (1980) definition of firm failure is legalistic, meaning that the main criterion is whether the firm has filed for bankruptcy or not. The sample excludes non-listed firms and companies operating in utilities, transportation or the financial sector. The study identifies four factors, which have a significant effect on the probability of the firm failing (within one year). The size of the firm decreases the probability of bankruptcy, while leverage has the reverse effect. Also, firms with superior performance measures, such as higher profitability and liquidity, were less likely to face bankruptcy.

Lukason (2006) has estimated the probability of bankruptcy in Estonian retail and wholesale companies by employing a logit analysis, but also a discriminant analysis and modern data-driven models such as neural networks and recursive partitioning. The failure definition is based on explicit data either on firm bankruptcy or liquidation due to non-compliance with the minimum net assets requirement over 2000–2003. The logit model, estimated on data about trade and services firms over the period 1995–2003, suggests that the best indicators for capturing the probability of bankruptcy were the firm's size, return on assets and cash flow to sales. All these measures decrease the probability of bankruptcy.

Survival models have become increasingly popular over recent years in several fields including bankruptcy prediction. Although certain data-driven methods, such as neural networks, recursive partitioning and others, can outperform the survival models in terms of prediction accuracy, they do not lend themselves to straightforward interpretation or generalization. Thus, for exploratory purposes the survival models are preferred. As claimed by Shumway (2001), hazard models are superior when compared to static models (including logit models) while accounting explicitly for firm survival spell. The survival models allow a firm's risk of bankruptcy to change over time. By applying a discrete data duration model, Shumway (2001) rejects the significance of many accounting ratios suggested as relevant for predicting bankruptcy in earlier studies (e.g. Altman, 1968; Ohlson, 1980). In addition, Shumway (2001) extends the list of covariates using market variables including firm relative market capitalization, past stock returns and the idiosyncratic standard deviation of stock returns. All market-based variables turn out to be significant predictors of firm distress.

Walker (2005) combines the discrete duration model and the structural model of Merton (1974), which improves the default prediction for US industrial machinery firms. The study also stresses the importance of accommodating firm-specific unobserved heterogeneity in default prediction models.

Campbell et al. (2005) employ monthly data on publicly listed US firms over the period 1963–2003 in order to predict firm bankruptcy and distress in a broader sense. Their study confirms that high leverage, low profitability and market capitalization, lower historical stock returns, more volatile past stock returns, lower cash holdings, higher market-to-book equity ratios, and lower prices per share indicate corporate distress and a high probability of bankruptcy. One of the authors' main contributions was the estimation of predictive variables for different horizons. This analysis revealed that market-data, such as a firm's relative market capitalization, market-to-book equity value and equity volatility, were the most robust indicators of forthcoming bankruptcy for longer prediction horizons.

Finally, the studies on firm demographics cast light on some related aspects of firm sustainability. The main focus in this line of research lies in explaining regional and industry-level variables influencing the lifespan of the firm with particular interest in the firm's growth and labour market issues. Like the corporate default oriented research, the results reinforce the significance of firm size and age as sustainability promoting factors (Masso, Eamets, Philips, 2004; Kaniovski and Peneder, 2007; Konings and Xavier, 2002). After all, Kaniovski and Peneder (2007) found that the Herfindahl concentration index enters negatively into hazard estimations using data for Austrian firms; however, the evidence from Estonia, according to Masso, Eamets and Philips (2004, 2006), and from Slovenia (Konings and Xavier, 2002), did not discover any statistically significant relation in that regard.

The remainder of this paper is organized as follows. Section 2 introduces the data and defines firm sustainability. Section 3 deals with descriptive data analysis and outlines the explanatory variables selection process. Section 4 discusses the methodology of survival analysis and presents the results along with consecutive discussion. Section 5 concludes.

2. Data description and definition of firm sustainability

This study employs Estonian Commercial Register data from 1994–2004, including the whole population of Estonian enterprises. For the purpose of this particular study, the selected sample contains only firms that meet the following criteria:

- Public and private[2] limited liability companies;

[2]Public limited liability companies (AS-type companies) are required to hold ten-times

- Firms that have borrowed at least once in any form (loan, leasing or issued debt) from the financial sector during the observation period;
- Active firms with positive sales over the financial year;
- Firms operating in manufacturing, trade and services, construction or real estate;
- Firms privately owned by domestic residents or foreigners. State owned firms are excluded;
- Firms were excluded if their financial revenues outnumbered the earnings from their main operations for most periods under observation;
- Firms, which have survived for at least 3 consecutive years.

The selection criteria above have filtered out firms that have unwanted properties. Firstly, companies that are not of the limited liability type have been excluded, because the rule of law imposes different rights and liabilities on them with important implications for the cost and probability of bankruptcy. Also, inactive firms and firms that have not qualified for any type of credit from the financial sector have been left out of the study. The aim of the research is to investigate the determinants of corporate sector failure, which have an effect on financial stability. Likewise, the study has excluded firms that are public owned and thus not budget constrained in the same way as firms in the private sector or belong to highly regulated industries. Finally, firms that are mainly engaged in financial-type activities and those whose lifespan is shorter than three years have been excluded from the analysis. The last cut in data occurs due to the lag structure of explanatory variables with the purpose of estimating firm failure with pre-determined data. Hence, all income statement data entered at the first lag and balance sheet variables as averages of the first and second lag.

In order to exclude the impact of outliers, the 1% lower and upper tail observations have been left out of the estimations separately for sustainable and distressed firms.

The final sample subject to survival analysis represents on average roughly 10% of firms in manufacturing, trade and services, real estate and construction sectors.

In most studies bankruptcy or firm failure is defined based on the rule of law, (e.g. the firm has filed for bankruptcy). Unfortunately, this indicator is

higher equity compared to private limited liability companies (OÜ-type companies), whose shares are not freely tradable.

often not available at individual firm level or on a timely basis. For Estonian firms, the registry data only contain information on firm bankruptcy and liquidation since 2003. The liquidation date of a firm, however, is a severely lagged distress indicator, which simply dates the end of lengthy bankruptcy proceedings. Data reveals that on average a firm is liquidated two years after falling short of the minimum capital requirement. A related problem documented by Lukason (2006) is the substantial improvement in the enforcement of Estonian bankruptcy law over time. Thus, the effective number of bankruptcies has been increasing in recent years with no underlying impairment to the financial standing of firms.

Several authors also employ a broader definition of default. For instance, Campbell et al. (2005) and Walker (2005) categorize firms in default as those delisted from major exchanges or those with a poor credit rating (D).

The proportion of firms listed on the stock exchange and for whom credit ratings data is available is very limited in the Estonian context. The data reveals that only about 3% of the firms under observation have been listed on the stock exchange, whereas the proportion within all observations in terms of firm-years is even smaller.

With the aim of investigating the threats on firm sustainability the definition of distress is based on the Estonian commercial code (§ 176), which says that firms must hold their equity above 50% of their nominal statutory capital. The minimum statutory capital for public limited companies was set at 100,000 Estonian kroons from 01.09.1995 to 01.09.1999. The respective capital requirement for private limited companies during the same period was 10,000 kroons. The requirement was increased to 400,000 kroons for public and 40,000 kroons for private limited companies after 01.09.1999 and has been the same since then. Thus, private and public limited liability companies whose minimum equity is less than half of the minimum required statutory capital are defined as non-sustainable. Default is defined as a situation where a distressed firm exits from the registry.

3. Descriptive analysis and selection of explanatory variables

3.1. Descriptive statistics

This subsection provides simple insight into the underlying data, while outlining the main properties before going to the estimations.

Figure 1 below depicts the historical dynamics of the number and share of assets broken down according to the definitions of distress and default as given in Section 2. As in survival analysis, the firms are censored after becoming distressed or having defaulted. All graphs show a higher rate of distress and default at the beginning of the observation period. The default rates are, however, many times lower compared to the distress rates. Hence, the number of firms falling short of the minimum required capital improved or managed to survive for some while. The asset-weighted graphs demonstrate lower hazard rates relative to the number of firms at risk. This shows that size matters or improves the outlook for survival. Moreover, whilst the distress rates decrease almost monotonically, in particular for the number of firms, then default rates demonstrate more dynamics over the years under observation. Obviously, the enforcement of law and the overall environment has considerable influence on whether the firm will stay in business or not.

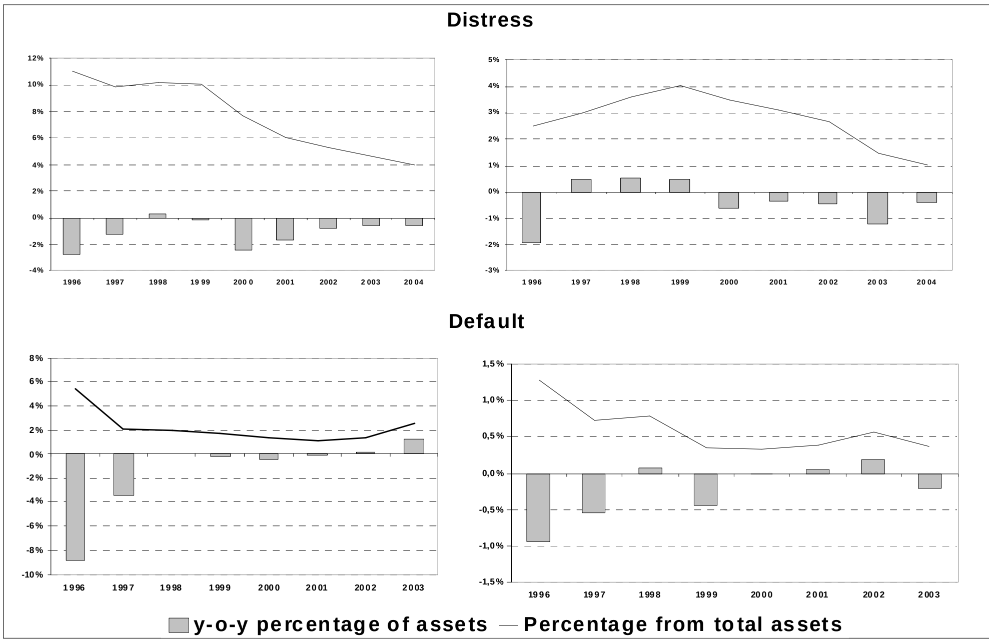

Figure 1: Historical conditional distress and default rates as a percentage from total number of corporations (left panel) and as a share of total corporate sector assets (right panel), 1996–2004

Since one of the study aims is to cast light on corporate sector sustainability from the perspective of financial stability, the structure of company liabilities including bank loans offers a good starting point for further analysis.

Figure 2 plots the dynamics and structure of corporate sector leverage over the last decade along with real GDP growth. The shortness of time series does not provide any statistically significant relationships between economic growth and leverage. Even though bank credit appears to be the most responsive to the economic cycle compared to other components of leverage. Bank credit and long-term bank credit in particular, shows a relatively strong positive correlation with economic growth, whereas the reverse is true for short-term liabilities including items such as funds owed to suppliers, interest and tax liabilities and other payments due. The dynamics of bank credit in relation to total assets is, however, not only explained by pro-cyclical movements, but also by the underlying financial deepening over the years under observation.

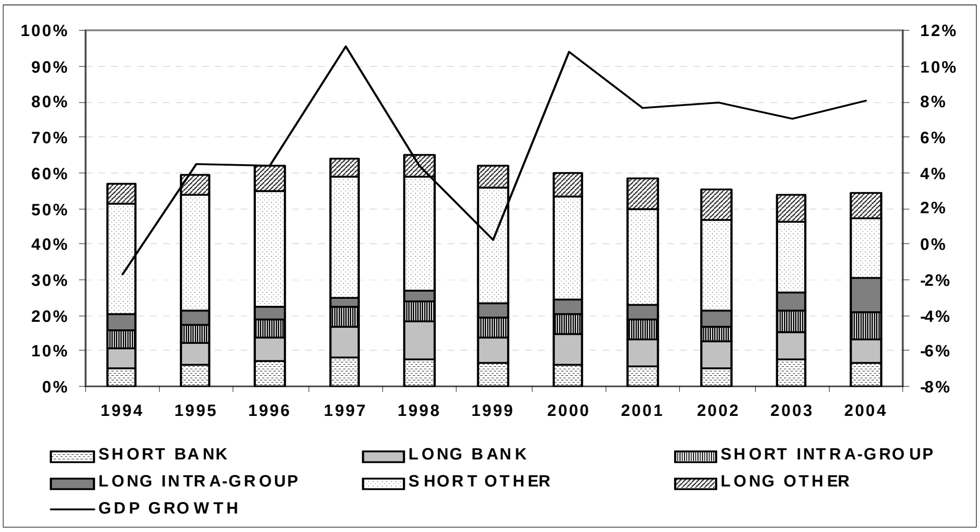

Figure 2: Total liabilities to total assets and the structure of leverage, 1994–2004 (bars), and real GDP growth (line, right scale)

Figure 3 demonstrates the dynamics and structure of leverage broken down by sectors. Leverage is highest in trade and services, with construction industry following close behind. The structure of leverage, however, reveals that an important proportion of the liabilities is composed of short-term trade credits or funds owed to suppliers in these industries. The share of bank credit is the smallest in the construction sector, although 2004 shows an increase similar to other industries, except manufacturing. Compared to other sectors, real estate firms are most strongly exposed to bank credit, which comprises about 1/5 of their assets. Intra-group funding is evident in all industries; however, construction stands out as the least dependent.

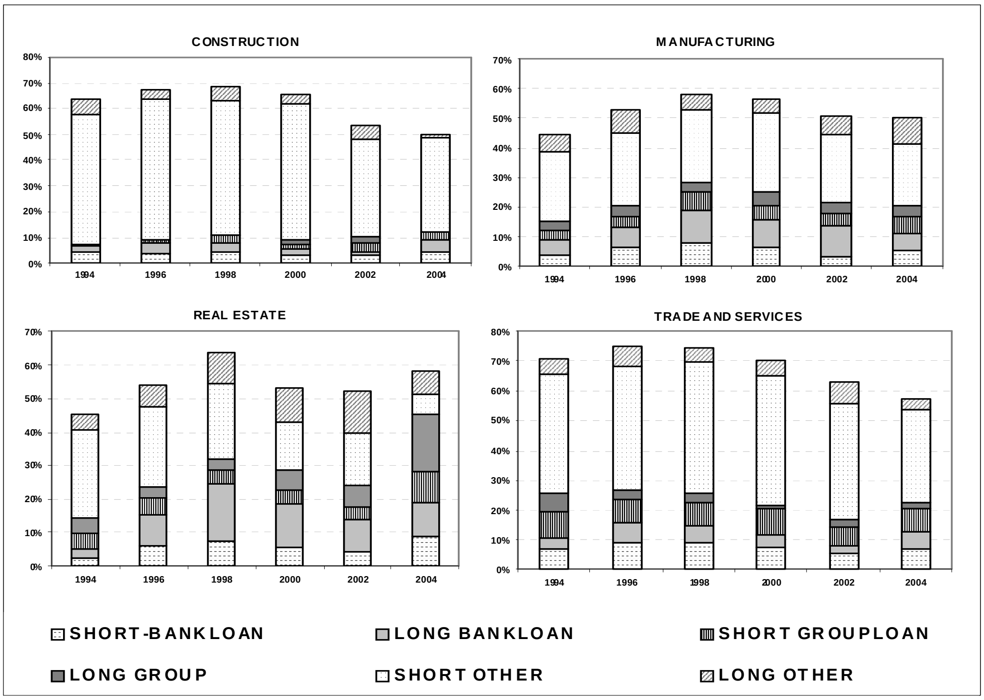

Figure 3: Total liabilities to total assets and the structure of liabilities grouped according to sector, 1994–2004

3.2. Selection of explanatory variables

The selection of independent variables is not straightforward. The early studies of Beaver (1966) and Altman (1968) employing simple discriminant methods suggested a wide variety of financial variables for predicting default. Recent research (Campbell et al., 2005; Walker, 2005) however, has cast doubt on the relevance of several financial variables, while demonstrating the superiority of market-based variables, which are also available at a higher frequency. The data in the Estonian Commercial Register only provides annual observations. This low frequency discounts the usefulness of accounting data and balance sheet data in particular.

The set of independent variables was chosen following three criteria: relevance based on past literature, straightforward interpretation and finally the presence of favourable estimation properties such as high response rate and small number of outliers. In the first step, the variables were controlled for their discriminatory power using the Wilxocon ranksum test (see summary statistics of explanatory variables in Appendix I, Table 3). Wilxocon test suggested that all variables given in Table 1 have statistically significant discriminatory power in regard to distress or default event or both. All explanatory variables will be lagged in the estimations. The balance sheet variables are the average of period *t–1* and *t–2,* obviously the periodic variables are simple one period lags *(t–1)*.

Literature has provided evidence that firm leverage and profitability ratios are robust predictors of firm distress (Sundararajan et al., 2002). The firms are also highly diverse in terms of structural characteristics, including features of the industry to which they belong. Masso, Eamets and Philips (2006), however, document in their study on Estonian firms that survival was explained rather by the characteristics of firms than the conditions of the industry structure. One of the variables widely shown to be of significance is firm size. Larger firms are less likely to fail, and this can be caused by numerous factors, such as their stronger funding base, higher diversification, larger cost of bankruptcy or better market position (Bernhardsen, 2001).

In the process of selecting variables, several alternative structural characteristics were considered. The Wilxocon ranksum test assigned weak discriminatory power to ownership type (foreign versus domestically owned firms) and a stock exchange listing dummy. Masso, Eamets and Philips (2006) claim that rather than foreign ownership itself, other variables, such as firm size, productivity and growth, matter. The number of firms listed was too small to provide any significant result.

From industry-level indicators, the Herfindahl concentration index was considered, since this measure has previously been used in firm demographics studies. Kaniovski and Peneder (2006) found that an increase in the Herfindahl concentration measure, a proxy variable of competition within the industry, had a negative effect on the survival of Austrian firms. Masso, Eamets and Philips (2006) however, demonstrated that the Herfindahl index was not a significant predictor of firm failure in Estonia. Lukason (2006) has noted that a large number of firms in Estonia are engaged in more than one field of business, and the classification scheme in the registry does not enable us to account for this variety in activities. Such a small domestic market does not provide the conditions for specialization. On the other hand, a small open market implies that export-oriented firms compete on foreign markets so that the domestic competition is not that relevant for them. Thus, the deficiencies in the recorded data and particularities of the small open market do not provide a good platform for investigating competitive pressure and its interaction with firm survival. Slovenia seems to be similar to Estonia in this respect according to Konings and Xavier (2002). They find that the Herfindahl index does not explain firm survival in Slovenia.

The structural indicators, which remained important in the selection process, include a public versus private limited company dummy and a deflated log size

Table 1: Model explanatory variables

Name	Description	Survival Expected sign	Evidence from previous literature
Structural characteristics			
Size	Log(total assets/GDP deflator)	+	Ohlson (1980), Masso et al. (2006), Bernhardsen (2001), Altman (2000), Kaniovski, Peneder (2006), Konings, Xavier (2002), Lukason (2006)
Limited company type	Public = 1 private = 0	unknown	
Leverage			
Broad	Total liabilities/total assets	-	Beaver (1966), Ohlson (1980), Bernhardsen (2001), IMF FSI (2006), Campbell et al (2005)
Bank credit leverage	Bank credits/(total debt+ equity)	-	
Profitability			
ROA	EBIT/total assets	+	Ohlson (1980), Bernhardsen (2001), Beaver (1966), Altman (1968), Altman (2000), Künnapas (1999), Campbell et al (2005), Lukason (2006)
Efficiency			
Sales-efficiency	Sales / operating costs	+	
Vulnerability			
Earnings volatility	Ln(ROA standard deviation)	-	

measured according to the firm's total assets. The size variable is mostly found to be statistically significant and positive in respect to firm strength and sustainability (see references in Table 1). As the present study incorporates data from both public and private limited liability companies, a dummy variable was used to capture the differences, which also turned out to be statistically significant in the majority of the estimations.

Leverage counts as one of the critical indicators in firm vulnerability, while also carrying a systemic aspect from the perspective of financial stability. Excessively leveraged firms can be vulnerable in the event of adverse shock, which may severely harm their debt repayment capacity (Sundararajan et al., 2002). Thus, a highly leveraged corporate sector entails strong spillover effects, which might affect the whole economy.

Also, several accounting variables were part of the selection process. A number of studies (including Beaver, 1966, Altman, 1968, Ohlson, 1980 and others) have suggested liquidity variables such as current ratio and working capital ratio.[3] The significance of both variables was rejected in the study by Shumway (2001), who claimed that the static models employed in previous research led to biased results. There is, however, a good reason to believe that low frequency balance sheet data, such as annual or quarterly observations,

[3]Current ratio = current assets/current liabilities; working capital ratio = current assets-current liabilities/total assets

cannot provide a good indication of the inherently volatile liquidity standing of a firm.

The IMF suggests the coverage ratio; that is, the ratio of earnings to interest and principal expenses, among the other core corporate sector soundness indicators (The Financial Soundness Indicators Compilation Guide, 2006). The downside of this measure lies in ambiguous interpretation, which violates the criteria of the selection process. As expected, the increase in the coverage ratio leads to an improvement in firm soundness and prolongs survival; however, for negative earnings the interpretation becomes blurred — the coverage ratio improves along with higher debt repayment costs, which is certainly a perverse implication.

As claimed by Rajan and Zingales (1995), corporate leverage can be measured in many different ways depending on the objective of the analysis. The broadest and most commonly used definition of leverage in other literature is the ratio of total liabilities to total assets. This can be viewed as an inverse proxy for what is left for the shareholders in case of liquidation. Rajan and Zingales (1995), however, warn that this measure does not provide a good indication of whether or not the firm is at risk of default in the near future. Instead, they suggest that leverage is the ratio of total debt to capital (defined as total debt plus equity). The rationale for choosing the narrow definition above is that accounts payable, which are part of the broad definition, are often used for transaction purposes rather than for asset funding.

Since corporate leverage is of particular interest from the perspective of financial stability, the bank-based leverage measure — debt owed to the financial sector (including leasing liabilities, loans and other debt owed to financial institutions) — has been used as a separate independent variable. Due to a high correlation between the broad and narrow definitions of leverage, all the estimations have been run separately for both measures of leverage.

Profitability is a key characteristic of a firm's ability to generate earnings, which can be used for servicing debt or expanding business. Profitable firms have better access to external finance, whereas negative profits, on the contrary, drain firm liquidity and put the solidity under pressure (Bernhardsen, 2001). Profitability, as in most of the papers referred to here, is measured in terms of return on firm assets.

In order to cover a broader set of firm characteristics, the measure of efficiency defined as total sales to total operating expenses was also found to be significant and positively related to firm sustainability. The alternative productivity or efficiency indicators based on personnel costs or number of employees produced insignificant or even counterintuitive results. This is arguably related to the substantial share of underreported personnel costs in the early years of transition.

Volatility as a reflection of instability and risk has been used as an indicator of corporate distress, although, measured using market data (Walker, 2005; Campbell et al., 2005). Due to the lack of stock market data, the vulnerability variable is calculated as a log-transformed historical standard deviation in returns on firm assets.

4. Survival analysis

4.1. Methodology

The aim of the study is to explore the effects of particular variables on the likelihood of firm failure. Therefore, methodology was selected from among models that allow good interpretation of the explanatory variables. One of the approaches recently favoured in the literature dealing with predicting corporate default is survival analysis, which also facilitates interpretation and generalization of the results in respect to particular sets of explanatory variables.

The modelling aspect of the study employs grouped data survival analysis based on complementary log-logistic distribution. Most of the data used in social sciences are continuous in time, but spell lengths are only observed in intervals such as weeks, months, quarters or even years (grouped or banded data). The length of the observation intervals relative to the typical or true spell length determines the choice between a continuous versus discrete time specification. The larger the ratio of grouped intervals relative to typical, real spell length, the more appropriate the use of a discrete time specification model. The standard continuous-time approach leads to biased results when used on grouped (observed in discrete intervals) or discrete data[4] (Jenkings, 2004). In the present study firm accounting data is only observed annually, which suggests the use of a discrete duration data analysis methodology.

The central concepts in survival analysis include the survivor and hazard functions (hazard rate). Given the discrete, yearly observations we observe firm *i*'s spell from year *k = 1* through to the end of the *j*-th year, at which firm *i*'s spell is either complete (the firm turns out to be unsustainable) or right censored (the firm exits the sample without experiencing the event). The survivor function reflects firm *i*'s probability of surviving beyond year *j*.

$$S_i(j) = Pr(T_i > j) \tag{1}$$

[4] Continuous-time models assume that failure times cannot tie or coincide, which is frequently observed in grouped data.

In discrete-time analysis, the hazard function or conditional failure rate is the probability that a failure event occurs within a given year j conditional on surviving until this particular year.

$$h_{ij} = Pr(T_i = j | T_i \geq j) \tag{2}$$

The data is left truncated (delayed entry), which means that firms are at risk since their establishment, while the data is observed only from 1994. All firms with delayed entry — that is, established before 1994 — are skipped, since estimating the model with unobserved heterogeneity does not account properly for left truncated data.

The lifetable method is used for investigating empirical time-dependent patterns of baseline hazard. Because the yearly intervals correspond with common financial and accounting cycles, then a lifetable method without interval-adjusted risk has been used in this study.[5] This is equivalent to the Kaplan-Meier product limit method for continuous time data. An estimate of the hazard rate is therefore:

$$\widehat{\theta}(j) = \frac{(\widehat{S}(j) - \widehat{S}(j+1))/(t_{j+1} - t_j)}{(\widehat{S}(k) + \widehat{S}(k+1))/2}, \tag{3}$$

where survival estimate $\widehat{S}(j) = \prod_{k=1}^{j} \left(1 - \frac{d_k}{N_j}\right)$ and d_j marks the number of failures in observed interval. N_j is the number at risk of failure at the start of the interval (Jenkings, 2004).

The estimation part applies a complementary log-log (cloglog) hazard function or discrete-time proportional hazard model with time-varying covariates. The drawback of cloglog is that the pattern of duration dependence or baseline hazard $c(t)$ cannot be precisely identified. Nevertheless, a complementary log-log model is the most commonly used one for dealing with intrinsically continuous but grouped data (Jenkings, 2004).

With a cloglog model, the regression coefficients lend themselves to proportional hazard rate interpretation. Having the underlying variables in percentage form means that the coefficient captures a proportional percentage change in the hazard given a one percentage change in the covariate. For log-measured covariates, the coefficient is expressed as the elasticity of the hazard with respect to a particular regressor. If the estimated model however, has omitted regressors or fails to account for unobserved heterogeneity, the model

[5] Interval adjustment would account for firms that leave mid-way through the relevant year, but can not be traced later. This is not the case with annual accounting data.

provides an under-estimate of the proportionate response, which is also no longer constant, but declines with time (Jenkings, 2004).

Hence, the standard cloglog model is generalized to allow for unobserved individual firm effects (u) leading to the following specification of a discrete time proportional model with unobserved heterogeneity:

$$c \log \log \left[h(j, X|v) \right] = D(j) + \beta' X + u \tag{4}$$

where the additional additive "error" of unobserved effect is $u = \log(v)$ and *v* accounts for an unobservable individual effect following distribution, which summarizes the variance in *v*. In the present study *v* is assumed to follow normal distribution. *D(j)* characterizes the baseline hazard function. $\beta' X$ includes the intercept term.

Thus, the cloglog hazard rate with unobserved heterogeneity (frailty) has the specification:

$$p(t) = 1 - \exp\left[- \exp\left(D(j) + \beta' X + u \right) \right] \tag{5}$$

4.2. Results of survival estimations

The empirical lifetable hazard functions, conditional on distress and default accordingly, suggest that the hazard rate or the probability of failure over the next year (conditional on being healthy up to the point under observation) decreases over time; however, not in a fully monotonic manner. Whilst the distress risk falls rapidly after the first years in business, the risk of defaulting vanishes more slowly and in a non-monotonic manner. The confidence bands widen in later spells. This is apparently caused by the smaller number of observations in later spells as the company continues to survive.

The most robust industry (see Appendix II, Figures 5 and 6) turns out to be manufacturing with the exception that during the first year of operation, construction firms demonstrate even greater vitality. Trade and services firms, on the contrary, are the most vulnerable, especially in early spells. This result is already known from previous literature. Masso, Eamets and Philips (2006) document that the exit rate for Estonian manufacturing firms is lower compared to services firms. A similar conclusion is drawn by Kaniovski and Peneder (2007), in their study on the exit rates of Austrian manufacturing and services firms. The hazard rate in the real estate and construction sectors is dropping at a relatively slower speed. Unfortunately, there is no known study that uses any comparable definition of hazard. Therefore, no comparisons can be made regarding the level of survival or hazard rates used in the present paper.

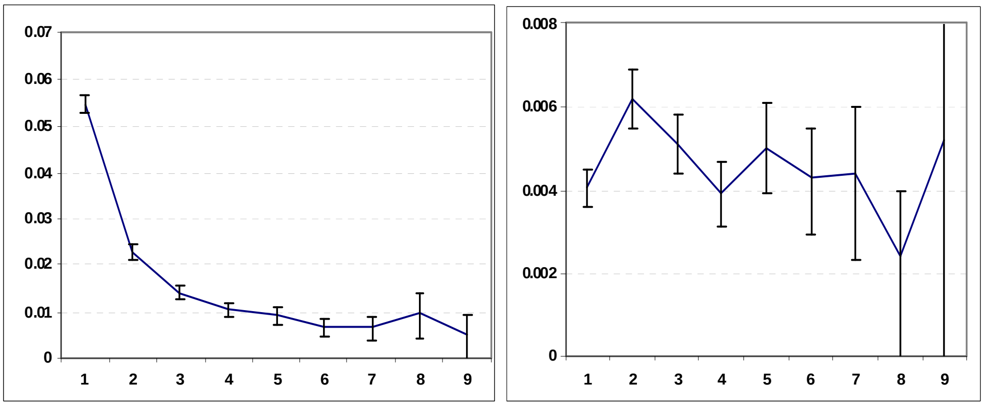

Figure 4: Lifetable hazard rate estimates 1996–2004 for distress (left panel) and default (right panel) firms established 1994 and later

All estimations, whether conditioned on a firm distress or default event, show strong results in respect to the regressed variables (see Table 2). Baseline hazard coefficients imply that while the distress hazard clearly decreases over time, the default baseline hazard is not precisely estimated. This is evidence of a non-monotonic pattern of the default hazard function.

The firm size variable is highly significant and negative in relation to the hazard. This implies that size matters and larger firms are less likely to become distressed as well as end up in default. This supports conclusions drawn in other literature (e.g. Altman, 2000; Ohlson, 1980; Lukason, 2006). The log measure of deflated total assets lends itself to an elasticity interpretation. Thus the coefficients averaging up to about 0.6–0.7 for distress based hazard estimates suggest that for every 10% increase in deflated total assets of the firm, the hazard ratio drops by 6–7%. The same elasticity for default hazard is as much as 8%. In an industry comparison, however, real estate and construction firms are exemptions, showing that size in these industries does not help them to escape default that much, although it protects firms from becoming distressed (see Appendix III, Tables 4 and 5).

After controlling for firm size and other variables, the private versus public limited company dummy still remains highly significant throughout all industry-aggregate estimations. Part of the reason here is that the definition of distress explicitly conditions for firm status — whether public or private. However, the strong and significant coefficients in default estimations cast doubt that this is the sole explanation. Evidence shows that public limited liability companies are not only more prone to violate the minimum capitalization

Table 2: Cloglog model estimations according to distress and default definitions, exponent-form coefficients

	DISTRESS		DEFAULT	
STRUCTURAL				
Baseline hazard	0.488*** (-4.19)	0.394*** (-5.43)	0.771 (-1.02)	0.826 (-0.77)
Ln(total assets/deflator)	0.545*** (-13.84)	0.679*** (-10.61)	0.769*** (-5.21)	0.747*** (-5.83)
Incorporation (base: private)	2.702*** (6.53)	1.463*** (2.69)	2.066*** (3.71)	2.149*** (3.90)
LEVERAGE				
Total liabilities to total assets	1.035*** (13.36)		1.002** (2.32)	
Bank debt to total capital		1.011*** (6.40)		1.007*** (10.06)
PROFITABILITY				
Return on assets	0.981*** (-8.29)	0.978*** (-9.95)	0.990*** (-4.66)	0.991*** (-6.37)
EFFICIENCY				
Sales/operating expenses	0.993*** (-2.95)	0.994*** (-2.81)	0.983*** (-6.76)	0.982*** (-7.10)
VULNERABILITY				
Ln(stdev ROA)	1.182*** (3.90)	1.034 (0.82)	1.004 (0.06)	1.023 (0.39)
DUMMIES				
Year	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes
MODEL STATISTICS				
Log Likelihood	-2220.62	-2310.43	-1255.86	-1230.16
Chi-square	205.17	175.94	88.81	203.00
Firm heterogeneity (p-value)	-	-	0.43	0.03
AUROC, %	87	79	73	71
Firm-years (failure)/firms	20040(568)/6767	20040(568)/6767	21628(282)/8116	21628(265)/8116

Note: z-values in brackets. *, **, *** indicate significance at the 10, 5 and 1% levels respectively

requirements, but they also exit more frequently compared to private limited liability companies. The coefficients are surprisingly high for both types — distress and default hazard. Seemingly, the high capital costs involved in public limited companies are not paid off on the thin and largely illiquid capital market. The alternative costs of re-capitalization for the owner of a public limited company are high relative to liquidation. Also, regulations have put more pressure on public companies relative to private ones. For example all public limited companies were forced to register themselves in the securities registry by mid-2003. The public firms that did not comply with this requirement were liquidated. It might also be argued that agency problems appear more often in public firms where the ownership and management are more separated.

Both leverage measures exhibit positive and precisely estimated coefficients relative to hazard ratio or risk that the firm will become distressed and eventually default. This implies that the firm's debt burden is of considerable importance from the perspective of financial soundness. Thus, the Estonian market provides access to external funding and firms excessively exposed to it are more prone to fail. This evidence resembles conclusions drawn on firm survival studies carried out in mature economies (Konings and Xavier, 2002).

A 10% increase in broad leverage increases the proportional distress hazard as much as 40% and default hazard by just 2%[6]. The coefficients for a bank debt based leverage variable reveal that a 10% increase in bank debt relative to firm total assets increases the risk of distress and default by 12% and 7% respectively. In general, leverage has stronger coefficients for explaining distress compared to default. This implies that a high debt level has a stronger effect on the firm probability of becoming undercapitalized, but not such a strong impact on the probability of default.

As expected, profitability turns out to be a key factor promoting firm sustainability. Firms with a higher return-on-assets ratio tend to be more robust, whereas a strong earnings base precludes firms falling short of capital. A 10% increase in return on assets corresponds with the distress hazard rate dropping to 80% and default hazard rate falling to 90% in proportional hazard terms.

The efficiency variable also works surprisingly well throughout all aggregate estimations. Here, however, the effect on default is larger compared to distress. A 10% improvement in efficiency helps to reduce the distress hazard down to 90% and the default hazard down to about 80% in terms of proportional hazard. The industry level estimations in the Appendices (see Appendix III, Tables 4 and 5) provide more support for the argument that the sales-to-costs variable is a stronger predictor of default than distress.

Volatility in asset returns is a positive function of distress hazard. Although, three out of four coefficients have an expected positive sign, only one of them is statistically significant. Hence, volatility seems to be least robust among selected indicators. Nevertheless, the significant coefficient implies that each 10% increase in volatility results in a 1.8% increase in distress hazard.

In general, distress is more obviously explained by financial variables, such as leverage, asset return and return volatility, whereas default is rather a function of operational deficiencies.

The AUROC (Area Under Receiver Operating Characteristics Curve) values reflecting the predictive power of models are weaker for estimations with bank debt based leverage compared to broad leverage definitions. Arguably banks screen out the worst firms, whereby high bank debt leverage contains two opposite signals — eligibility for bank credit and indebtedness. On the other hand, distress is better predicted compared to default, but this might be

[6] A 10% increase in explanatory variable corresponds with β^{10}.

the case because default is a less frequent event.

5. Conclusions

The study confirms the stylized fact that firms in general are more vulnerable in their start-up period. Firm distress, meaning the failure to meet the regulatory minimum capital requirements is a time-decreasing function. Firm default or exit after failing to meet capital requirements is, however, a non-monotonic time-decreasing function implying a lagging hazard in terms of distress. This seemingly refers to some regulatory enforcement issues. At the industry level, manufacturing turns out to be the most robust, as opposed to the trade and services sector, which is exposed to the highest risk during early spells in particular. The decrease in the hazard rate in the real estate and construction sectors, however, is slower relative to the manufacturing, trade and services sectors.

The dynamics and structure of firms' aggregate leverage shows that debts and long-term debts in particular, owed to banks or other financial institutions, are the most pro-cyclical component of leverage. Economic downturn is reflected in the increased share of short-term payables due, such as payables to suppliers, tax authorities and accrued interest. In an industry comparison, trade and services firms are the most leveraged; however, a major part of their liabilities are short-term and non-debt or transaction related. The most bank-debt exposed sector is the real estate industry.

The survival analysis demonstrates that firm sustainability in Estonia is a positive function of high and stable asset return, low leverage, good efficiency and a large assets base. The majority of these variables show statistically significant results over a range of estimations, whether conditioned on a distress or default event. Volatility in return on assets was the only less robust predictor. Interestingly, there appears to be a significant difference between public and private limited companies. While controlling for the size of assets, the results suggest that public limited companies are more prone to face distress and eventually default. Arguably, this is an implication of the higher capital costs for public limited companies, which are not compensated for by the shares trade option on an inactive and thin capital market. Moreover, regulations have put more pressure on public companies relative to private ones, since the firms that did not comply with the requirements were ultimately liquidated. The Herfindahl index, a proxy for competitive pressure in a particular industry, did not reveal any significant relationship to firm distress or default.

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Appendix I

Table 3: Summary statistics of key explanatory variables grouped according to the distress and default definitions

Explanatory variables	Non-defaulted firms				Defaulted firms				Wilxocon Ranksum test Z-value
	Mean	Median	Stdev	Obs	Mean	Median	Stdev	Obs	
Log(Size)	14.12	14.06	1.68	45425	13.21	13.17	1.59	462	10.45
ROA	0.11	0.08	0.24	45425	-0.15	-0.03	0.43	462	-19.98
Efficiency	1.01	1.01	0.26	45425	0.87	0.96	0.29	462	-7.35
Broad leverage	0.61	0.63	0.32	45425	1.02	0.90	1.06	462	16.23
Bank leverage	0.19	0.03	0.28	45425	0.50	0.22	0.78	462	12.55
Volatility in ROA	0.18	0.12	0.50	45425	0.60	0.15	2.62	462	-2.83
Ownership (Base: foreign)	0.92	1	0.27	45425	0.96	1	0.19	462	0.43
Listed on stock exchange	0.00	0	0.04	45425	0	0	0	462	-4.37

Explanatory variables	Non-distressed firms				Distressed firms				Wilxocon Ranksum test Z-value
	Mean	Median	Stdev	Obs	Mean	Median	Stdev	Obs	
Log(Size)	14.19	14.13	1.66	43306	12.83	12.73	1.52	2581	40.22
ROA	0.12	0.08	0.22	43306	-0.16	-0.05	0.46	2581	45.27
Efficiency	1.02	1.01	0.26	43306	0.87	0.95	0.28	2581	35.45
Broad leverage	0.59	0.62	0.25	43306	1.03	0.93	0.88	2581	-52.98
Bank leverage	0.18	0.04	0.25	43306	0.36	0	0.70	2581	0.28
Volatility in ROA	0.16	0.11	0.18	43306	0.55	0.19	2.23	2581	-22.61
Ownership (Base: foreign)	0.92	1	0.27	43306	0.94	1	0.25	2581	-3.06
Listed on stock exchange	0.00	0	0.04	43306	0	0	0	2581	0.19

Appendix II

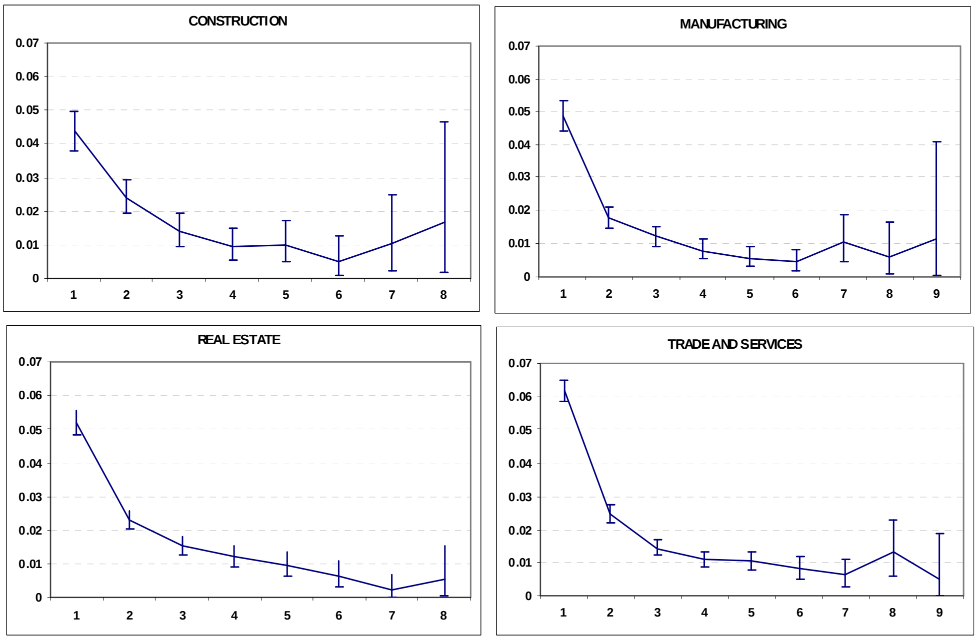

Figure 5: Lifetable charts by industry according to distress definition

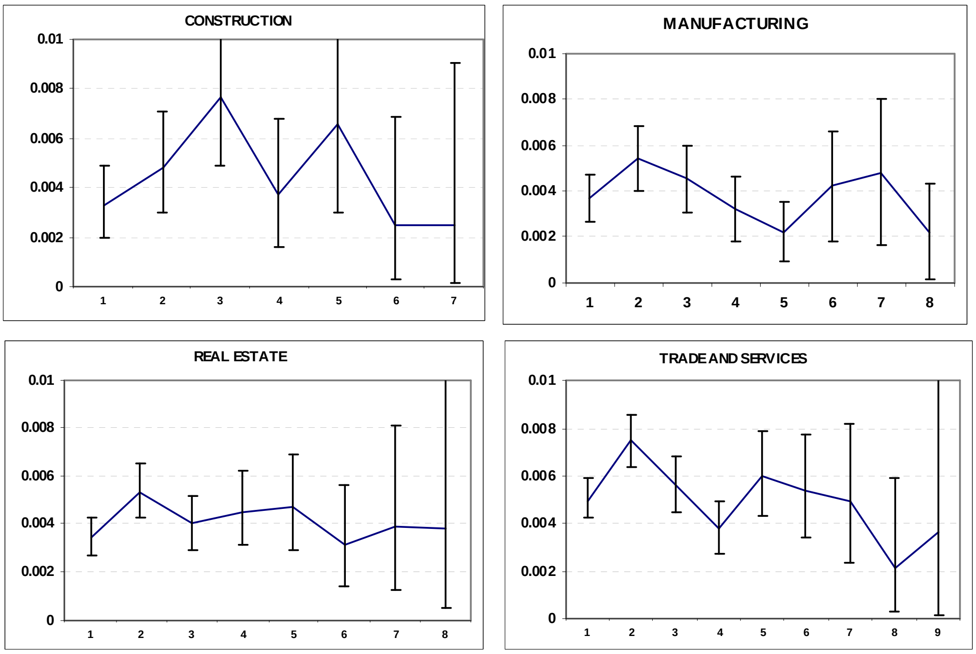

Figure 6: Lifetable charts by industry according to default definition

Appendix III

Table 4: Estimations with complementary log-log (cloglog) model using distress event, coefficients in exponent form

Indicators:	**DISTRESS**							
	Manufacturing		**Trade and services**		**Real estate**		**Construction**	
STRUCTURAL								
Baseline hazard	1.124 (0.16)	0.476* (-1.83)	0.657 (-1.10)	0.436*** (-3.33)	0.447** (-2.30)	0.366*** (-2.89)	0.330 (-1.39)	0.276* (-1.62)
Ln(total assets/deflator)	0.379*** (-3.95)	0.579*** (-5.70)	0.474*** (-6.71)	0.665*** (-7.48)	0.654*** (-5.55)	0.777*** (-3.83)	0.488*** (-2.72)	0.638** (-2.04)
Incorporation (base: private)	3.942*** (2.45)	1.593 (1.31)	3.89*** (4.86)	1.666*** (2.46)	1.608* (1.61)	0.995 (-0.02)	6.318** (2.35)	3.190* (1.73)
LEVERAGE								
Total liabilities/ Total assets	1.056*** (4.00)		1.045*** (6.75)		1.025*** (5.82)		1.041*** (2.77)	
Bank debt/ Total capital		1.016*** (3.91)		1.01*** (4.07)		1.006* (1.87)		1.020** (2.13)
PROFITABILITY								
Return on assets	0.978*** (-2.96)	0.975*** (-4.41)	0.972*** (-6.37)	0.970*** (-7.91)	0.989*** (-2.61)	0.988*** (-3.21)	0.980** (-2.25)	0.975*** (-2.63)
EFFICIENCY								
Sales/operating expenses	0.986 (-1.49)	0.995 (-0.73)	1.001 (0.10)	1.000 (0.07)	0.989*** (-3.59)	0.988*** (-3.77)	0.994 (-0.52)	1.001 (0.10)
VULNERABILITY								
Ln(stdev ROA)	1.443** (2.30)	1.164 (1.45)	1.161** (2.03)	0.970 (-0.50)	1.160* (1.86)	1.064 (0.81)	1.370* (1.64)	1.088 (0.54)
DUMMIES								
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
MODEL STATISTICS								
Log Likelihood	-366.87	-386.36	-1015.11	-1063.86	-587.93	-605.92	-220.27	-225.71
Chi-square	19.94	43.86	71.35	89.73	60.14	51.60	11.75	11.95
Firm heterogeneity (p-value)	0.07	-	0.20	-	0.50	-	0.17	0.29
AUROC, %	84	79	87	79	82	74	81	71
Firm-years (failure)/firms	4149(95)/1413	4149(95)/1413	9129/(264)/3132	9129/(264)/3132	4915(151)/2043	4915(151)/2043	1847(58)/681	1847(58)/681

Note: Indicator "Firm-years(failure)/firms" the number of firms summed up over industry estimations is larger compared to the number of firms in aggregate estimations because some firms have redefined their main sector of industry during the observation period.
z-values in brackets. *, **, *** indicate significance at the 10, 5 and 1% levels respectively

Table 5: Estimations with complementary log-log (cloglog) model using default event, coefficients in exponent form

Indicators:	**DEFAULT**							
	Manufacturing		**Trade and services**		**Real estate**		**Construction**	
STRUCTURAL								
Baseline hazard	0.883 (-0.20)	1.287 (0.28)	1.186 (0.46)	1.055 (0.15)	1.368 (0.60)	1.345 (0.60)	0.055*** (-3.39)	0.071*** (-3.04)
Ln(total assets/deflator)	0.659*** (-3.27)	0.560** (-2.11)	0.687*** (-4.82)	0.692*** (-4.79)	0.881 (-1.32)	0.836* (-1.91)	0.986 (-0.09)	0.916 (-0.53)
Incorporation (base: OÜ)	3.021** (2.26)	4.822* (1.85)	2.910*** (3.77)	2.683*** (3.51)	0.875 (-0.28)	0.954 (-0.10)	3.702** (2.25)	4.897*** (2.54)
LEVERAGE								
Total liabilities/ Total assets	1.000 (0.05)		1.009*** (5.40)		1.003** (1.92)		1.004*** (2.46)	
Bank debt/ Total capital		1.011* (2.07)		1.008*** (6.49)		1.006*** (4.43)		1.013*** (5.48)
PROFITABILITY								
Return on assets	0.990*** (-2.84)	0.983** (-2.32)	0.993*** (-2.92)	0.991*** (-3.77)	0.994** (-2.28)	0.993*** (-2.94)	0.991** (-2.35)	0.991* (-1.96)
EFFICIENCY								
Sales/operating expenses	0.984** (-2.10)	0.982* (-1.85)	0.984*** (-4.13)	0.984*** (-3.83)	0.982** (-4.35)	0.982*** (-4.50)	0.973*** (-3.12)	0.972*** (-3.16)
VULNERABILITY								
Ln(stdev ROA)	1.119 (0.76)	1.106 (0.52)	0.915 (-1.11)	0.937 (-0.78)	1.130 (1.02)	1.197 (1.54)	0.972 (-0.17)	0.966 (-0.20)
DUMMIES								
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
MODEL STATISTICS								
Log Likelihood	208.58	205.78	-601.03	-596.29	-285.79	-283.47	-127.13	-117.19
Chi-square	36.09	8.90	100.25	100.02	36.45	54.54	22.96	32.81
Firm heterogeneity (p-value)	1.00	0.14	0.12	0.13	0.33	0.28	0.32	0.07
AUROC, %	69	59	76	72	69	69	63	61
Firm-years (failure)/firms	4182(44)/1610	4182(44)/1610	10121(129)/3854	10121(129)/3854	5461(61)/2419	5461(61)/2419	1864(31)/780	1864(31)/780
Average life-spell per firm	4.6	4.6	4.6	4.6	4.3	4.3	4.4	4.4

Note: z-values in brackets. *, **, *** indicate significance at the 10, 5 and 1% levels respectively