FIRM'S PERFORMANCE ANALYSIS USING SURVIVAL METHOD

by

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Abstract

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This work addresses the question of firm's performance and its probability of failure by employing a new approach basing on the Ukrainian joint stock companies of the non-financial sector. We use the discrete non-parametric proportional hazard model in order to be able to study the impact of the negative performance spell length in addition to traditionally used firm's characteristics, such as liquidity, leverage, size, age and ownership.

We find that there is a significant duration dependence in the firm's negative performance. In the models which use firm's growth as indicator of performance the duration dependence is positive, whereas profitability models show, that the probability of negative performance in the next period increases with the spell length up to some point, and then decreases. So, the firm can't experience losses for a too long time: either its profits become positive or the firm exits. We also find that such firm's characteristics as liquidity, size and age decrease the probability of failure.

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Chapter 1

INTRODUCTION

The question of the firm performance is very important for different groups of people. All agents that have to make any financial decisions about a company are concerned with its financial position. Thus, owners, managers, potential investors, banks, other financial institutions, creditors, business partners, employees, and government are interested in models that help to analyse and predict the performance of the companies.

Lizal (2002) states three reasons of firm's failure: wrong asset structure, wrong financial structure, corporate governance problems. According to the neoclassical approach bankruptcy is an instrument for reallocation of resources from inefficient to efficient use. By going bankrupt a firm frees the wrongly allocated resources for their more efficient use within the same or even another industry. Another reason for firm's bankruptcy may be wrong financial structure, even if the asset structure is appropriate. This means that firm goes bankrupt in the short run, even though it would survive in the long run (the quality of the capital markets is important in this case as they could provide some support for temporarily financially constrained firms). There is also a corporate governance problem, which often leads to bankruptcy, but changing the management of the firm would be a better solution in such case.

Creditors (banks, different financial institutions, business partners, suppliers) are interested in predicting bankruptcy of the company as a means of risk management. They should be able to evaluate the credit quality of the company in order to adjust the contracts and create the appropriate reserves.

Owners, managers and potential investors should have a good control of the firm's position in order to be able to make strategic decisions about the firm: investing decisions, assets or financial restructuring, change of management, or exit.

The failure probability prediction has been a real challenge for empirical and theoretical researchers for many decades. Even though the theoretical underground remains very low, there are a lot of works in empirical analysis.

Most of the modern empirical works are based on hazard (or survival) model, which has a number of advantages: it controls for a period at risk of a firm, the explanatory variables may vary over time, the results are consistent and the forecast is more efficient (e.g. Shumway (2001)).

Recent works, show that accounting based and stock market information as well as macroeconomic indicators are important for bankruptcy prediction (Duffie and Wang, 2004), Hillegeist et al 2004)).

However, most of the works concentrate on the developed economies. However, the institutions are very important factor in the performance analysis. These includes tax law, bankruptcy law, soft budget constraints, contract enforcement and court systems, financial markets development, capital accessibility, corruption etc. The difference in the institutional environment determines the need in studying the transition countries.

Perederiy (2006) proposes the logistic bankruptcy prediction model, which finds the accounting-based information to explain the probability of firm's failure.

This thesis will provide the empirical analysis of the firm's performance and probability of failure using the survival methodology. We will use the data set of Ukrainian non-financial JSC companies.

With the duration analysis we will incorporate the information on the length of a spell the firm has experienced negative performance in addition to the traditionally used accounting-based and general information such as liquidity, leverage, size, age, ownership and industry of the firm. We will build the discrete non-parametric proportional hazard models to estimate the probability of firm's failure or probability of a firm to have negative performance in the next period, given that its performance was negative several periods before. The pattern of duration analysis will be studied, that is how the probability of the failure changes depending on a spell length, regardless of the firm's characteristics. And then we will study how firm's characteristics change the hazard of failure for each spell length.

The work is organized in a following way: in Chapter 2 we review the relevant literature, Chapter 3 provides the methodology and data description. We present our empirical results in Chapter 4. Chapter 5 concludes.

Chapter 2

LITERATURE REVIEW

Western economists have started studying the firm's performance and failure question in the late '60s. They distinguish between theoretical and empirical works in this field. We start with the theoretical models. Then empirical models will be considered according to the methodology classification. Linear and qualitative-response models will be presented briefly. More attention is going to be paid to hazard models, which correspond to the methodology of the thesis. Then we'll consider the specificity of firm performance in transition economies and Ukraine in particular.

Among **theoretical works** the single-period models, gambler's ruin models, models with perfect access to external capital, and models with imperfect access to external capital are considered to be the core works (classification by Scott (1981)):

According to *single-period models*, the firm will go bankrupt if its value at the end of the period will be less than it owes its creditors: $V < D$. Black-Scholes (1973, 1974) and Merton (1974) model is similar to this model, but the dept of a firm is a single discount bond.

Gambler's ruin models (Borch (1967), Tinsley (1970) etc) assume that firm's capital (K) increases from positive cash flow, and the firm can cover its losses only by selling assets (no access to the stock market). So, the firm will go bankrupt if K is negative: $K+Z<0$, where K – liquidation value of the stockholder's assets, Z – change in K.

Models with perfect access to external capital (Scott (1976, 1977)) predict the firm fail if the expected loss is greater than the optimal level of equity (ignoring loss) in the next period (otherwise, firm may issue additional equity to cover the loss): S+X<0, where S – optimal value of equity next period, X – next period earnings (loss).

Models with imperfect access to external capital consider periods 0,1, and 2. The firm will be liquidated in the period 2. The firm will fail in period 1 if the stockholder wealth reaches zero: $S_1[\underline{I}_1] + (1+c)(X_1[K_0] - \underline{I}_1) \leq 0$, where $S_1\lfloor \underline{I}_1 \rfloor$ - market value of the firm's equity at period 1, depending on $\underline{I}_1$ - optimal level of investment, given that firm uses external sources of capital; c- floatation costs per unit of equity, $X_1[K_0] - \underline{I}_1$ is paid to stockholders as dividends ($X_1[K_0]$- firm's income in period 1, given K_0 - firm's capital in period 0).

Scott (1981) tried to integrate theoretical and empirical approaches in bankruptcy research, which had little in common before. Empirical works were believed to have no theoretical grounds. He concludes that 'Although the overlap between the empirical and theoretical models is imperfect, it provides empirical support for existing theory as well as theoretical justification for the bankruptcy prediction models.' He founds that empirical models in fact support the gambler's ruin model, model with perfect and imperfect access to external capital.

Depending on the methodology in use, **empirical works** are classified on linear, qualitative-response and hazard models (classification by Duffie and Wang (2004), Scott (1981)).

Beaver (1966, 1968) and Altman (1968) were first to build the *discrimination models* – linear models, that allow to classify companies as potential bankrupts and not. Beaver (1966) has started with the single ratio models, which used single financial ratios based on the accounting data to predict the failure of the company. In 1968 he used also the stock market prices for prediction. Altman (1968) introduced the famous "Z-score", which was used to discriminate between healthy companies and not. It was obtained through multiple discriminant analysis (MDA) using the information of several financial ratios simultaneously. Out of 22 variables, 5 were concluded to do explain the bankruptcy the best: Working capital/Total assets (WC/TA), Retained Earnings/Total assets (RE/TA), Earnings before interest and taxes/Total assets (EBIT/TA), Market value equity/Book value of total debt, Sales/Total assets. This work gave a great push to hundreds of researches on bankruptcy prediction, which is still relevant nowadays.

The work of Ohlsen (1980) is considered as an example of *conditional logistic* failure prediction models. The logistic probability function is used for predicting, which doesn't require any assumptions about the distribution of explanatory variables and its outcome can be interpret more intuitively rather than score result, given by MDA. Nine financial ratios, based on accounting information were considered in the Ohlsen's model, which is often referred to as "O-score".

Most of the modern empirical works on bankruptcy are based on the *hazard models*. Hazard bankruptcy model estimates the time, which is spent by a firm in the healthy group.

Shumway (2001) refers to the linear and logistics models discussed above as to static models with multi-period data, and argues that they produce biased and inconsistent estimates. When using these models one has to chose when to observe the firm (the most often - year or two before bankruptcy), which causes the selection bias. Shumway (2001) proposes to use hazard models which predict the probability of failure of a firm at each period. Three advantages of hazard model are stated in the work:

- it controls for a firm's period at risk;

- each firm's time series data is used, so it allows firm's characteristics to vary over time. Also, it allows macroeconomic indicators, which are the same for all firms and accounts for possible duration dependence;

- hazard model gives more efficient out-of-sample forecasts, as it makes use of more data.

Discrete-time hazard model can be interpreted as multiperiod logit model. The author suggest a discrete-time hazard model, using two accounting variables (NI/TA and TL/TA) and three market variables (firm's market capitalization, past excess stock returns, and the idiosyncratic standard deviation of the stock returns), which performs better out of sample than the alternative models (MDA with accounting variables, hazard model with just accounting or just market variables) and produces consistent estimates.

As it was stated previously, hazard methodology gave the opportunity to include macroeconomic variables into analysis. This allows controlling for the business cycle influence on the probability of bankruptcy, the importance of which is unambiguous: the probability of bankruptcy increases in the downturn of the business cycle. Duffie, Saita and Wang (2007) provide examples of the macroeconomic variables used in previous bankruptcy researches. Among them are: GDP growth, industrial production growth; national rate of corporate bankruptcies; interest rates, aggregate corporate earnings and others.

A number of papers attempted to find the empirical support for a theoretical Black-Sholes-Merton model, stated above, using discrete hazard function. However the theoretical underground of the issue remains weak.

Hillegeist, Keating, Cram, and Lundstedt (2004) compares theoretical Black-Sholes-Merton model (BSM), which is based on the market information only, with empirically derived accounting based "Z-score" and "O-score" models. The key factors included in the BSM model are market value of asset volatility and market-based leverage ratio. They found that BSM models performs better than others and is very convenient in cross country analysis, as it avoids the difference in accounting standards problem. However, it was found that BSM model doesn't contain all the bankruptcy relevant information. The alternative model, which included "BSM-score" in combination with either "Z-score" or "O-score" and annual interest rate, had greater explanatory power. This was explained by measurement errors (due to the estimation of dependent variables) and misspecification error (due to the assumptions violations) in the BSM model.

The key factor in hazard model of Duffie and Wang (2004) is distance to default, which is based on BSM model, and is the volatility-adjusted leverage (the number of standard deviations of asset growth by which market value of assets exceed standardized value of liabilities). They also found firm's net income to total assets ratio (NI/TA), firm's size, average for the sector NI/TA, and personal income growth (as a measure of the macroeconomic performance) to be important in bankruptcy prediction. In Duffie, Saita and Wang (2007), which is the extension to the previous paper, the model with distance to default, firm's trailing one-year stock return, 3 months Treasury bill rate and trailing one-year return on the S&P 500 index is proposed, which was concluded to have the improved out of sample performance, comparing to previous models.

The superiority of the hazard methodology was admitted by the modern researches. Thus, nowadays hazard models are the most popular in failure prediction. However most of the works are based on the Western economies and heavily rely on the stock market information.

The institutions are very important factor in the performance analysis. These includes tax law, bankruptcy law, soft budget constraints, contract enforsment and court systems, financial markets development, capital accessibility, corruption etc. The difference in the institutional environment determines the need in considering the **transition countries** separately.

Most of the works on transition countries use simple logistic methodology.

Hainz (2005) showed that the number of bankruptcies in transition countries is lower due to the low development of the institutions. They determine the creditor's incentives to start the bankruptcy procedure against the debtor. Weak institutions provoke passiveness of the creditors, which creates soft budget constraints for the inefficient firms. Thus, the efficient law environment and institutions which would eliminate the asymmetric information problem (e.g. credit registers).

Lizal (2002) found that the classical bankruptcy prediction accounting-based variables had little explanatory power for Chech Republic bankruptcy cases. The importance of the way of the privatization (mass voucher privatized firms tend to have higher probability of bankruptcy) and evidence of the soft budget constraints were found.

Most of the models for the Western firm's performance rely on the stock market information. However, despite being very fast growing, Ukrainian stock market is still small and weakly developed. It exists for about 10 years, and as any emerging marked is characterised by high returns with high volatility. Ukrainian stock market is poorly regulated, and lacks liquidity and capital supply (Ryzhkov, 2007). Only 350 companies' equity securities are listed on PFTS (First Ukrainian Trading System), which conducts about 95% of Ukrainian stock market operations. Thus, the market can hardly can be called efficient (prices on which fully reflect the available information (Fama, 1970)), as the main efficiency conditions (e.g. low transaction cost, legal investors' protection, low information cost, increasing number of high liquid securities (Fama, 1970)) are violated. So, the models which use the stock market information and rely on the assumption of the stock market efficiency can't be applied for Ukrainian companies performance analysis.

There is a few works on the failure of Ukrainian companies.

Perederiy (2006) introduced a logit model of the bankruptcy forecast for the Ukrainian companies. He included the financial indicators based on the balance sheets and income statements of the Ukrainian JSCs. One indicator for each category (size, profitability, liquidity, operational efficiency, capital utilization) was chosen. He also controlled for industry and business cycle. All coefficients were statistically significant.

Nicolsko-Rzhevskyy (2003) built both logistic and hazard bankruptcy prediction models. Besides the financial indicators the influence of the managerial efficiency is also included. However, bank bankruptcy prediction differs significantly from the companies in non-financial sector as the financial structure of them is very different.

Survival analysis for the non-financial sector of Ukrainian economy has never been done. In this work a survival time model for Ukrainian JSCs companies is going to be built. We will analyse the negative performance of the firms and the probability of their failure using accounting-based indicators, and general information on the firm such as its age, industry in which it operates. We will also control for the business cycle.

Chapter 3

METHODOLOGY[1] AND DATA

Survival analysis is used to study the length of the time spent by individual within some state. It models the "time to event" or "time to failure", which is also the spell length. In this work event – is not leaving the negative performance spell. So, the probability of negative performance in the next period, conditional on having the negative performance one, two, three etc. periods before will be modeled.

In our case the survival is continuous. However, the information is available only annually, thus we have grouped (or banded) data and the discrete hazard model should be used.

The discrete hazard rate $h(a_j)$ is the probability of exit in the interval $(a_{j-1}, a_j]$

$$h(a_j) = \Pr(a_{j-1} < T \le a_j \mid T > a_{j-1}) = \frac{\Pr(a_{j-1} < T \le a_j)}{\Pr(T > a_{j-1})} = \frac{S(a_{j-1}) - S(a_j)}{S(a_{j-1})}$$

Where $\Pr(T > a_{j-1}) = 1 - F(a_{j-1}) = S(a_{j-1})$ - the value of the survival function at the beginning of the interval. Correspondingly, $S(a_j)$- at the end of the interval. F (.) – is a corresponding failure function. For the data with the unit-length interval $(a_j - 1, a_j]$ the hazard rate is denoted as h_j.

[1] We will follow the methodology provided by Jenkins, S. http://www.iser.essex.ac.uk/teaching/degree/stephenj/ec968/

The discrete time survival function which shows the probability to survive until the end of interval j is:

$$S_j = \prod_{k=1}^{j}(1-h_k)$$

And the density function is the probability of exit within interval j is equal to the probability of surviving up to the end of period (j-1) times probability of exit at period j:

$$f(j) = \Pr(a_{j-1} < T \le a_j) = \frac{h_j}{1-h_j}\prod_{k=1}^{j}(1-h_k)$$

Taking into the account the continuous nature of the data, Jenkins (2004) proposes the discrete time representation of the continuous survival hazard rate, which satisfies the separability assumption, according to which the hazard rates are proportional:

$$\theta(t, X) = \theta_0(t)\exp(\beta' X) = \theta_0(t)\lambda$$

$\theta_0(t)$ - the baseline continuous hazard, which depends on time. It reflects the 'duration dependence', which is assumed to be the same for all firms;

λ - is the function of covariates X, which are specific for each firm. This function scales the baseline hazard.

Then the RHS of the expression

$$\frac{\theta(\bar{t}, X_i)}{\theta(\bar{t}, X_j)} = \exp(\beta' X)$$

is known as a hazard ratio and reflects the proportional effect of the absolute changes in covariates X on the hazard. And estimated β s show the proportional effect of the absolute changes in covariates X on the log of hazard ratio.

Thus, the following expression for the unit-interval hazard rate is derived:

$$\log(-\log[1-h_j(X)]) = \beta' X + \gamma_j$$

$$h(j, X) = 1 - \exp[-\exp(\beta' X + \gamma_j)]$$

where γ_j is the log of the integral of the baseline hazard, evaluated at the beginning and the end of the interval $(a_j - 1, a_j]$. γ_j reflects the duration dependence in the interval hazard, but in order to recover the continuous hazard one must make assumptions about the specification of the γ_j. By restricting γ_j in a proper way the model may turn into the continuous parametric model. In this work the discrete non-parametric specification will be used, which is appropriate for grouped data with quite long intervals.

The $\log(-\log(.))$ transformation is called 'complementary log-log transformation' and the discrete time proportional hazard model is often called 'cloglog model'.

Thus, the model will have the following specification:

$$c\log\log[1-h\ (j, X)]) = \beta' X + \gamma_J D_J\ ,$$

where Dj is a vector of the dummy variables, which correspond to the every survival time j.

Thus, according to Jenkins (2004) the discrete time hazard model can be estimated using the standard binary dependent variable models, as their likelihood functions are the same, given that the data is in the 'person-period' format, exactly as the panel data is:

$$LogL = \sum_{i=k}^{n} \sum_{k=1}^{j} [y_{ik} \log h_{ik} + (1 - y_{ik}) \log(1 - h_{ik})]$$

The major advantage of the using the hazard model is that each firm contributes several times to the likelihood function – each time it is at risk (if the firm didn't died this period, in the next period it is in the risk pool again) (Kennedy, 1998).

For the hazard models the unobserved heterogeneity is also important to be considered. If it is not considered, the hazard model assumes that the probability of exit is fully explained by the observed variables, included into the model. However, there are characteristics that either can't be measured, or are omitted because of the lack of data. Also, the observable variables may contain measurement errors. If the unobserved heterogeneity is important but not accounted for the model will produce the biased estimates. So, Jenkins(2004) modifies the discrete hazard model to account for the unobserved heterogeneity effects. Now the model will be:

$$c \log \log[1 - h\ (j, X \mid v)]) = \beta' X + D(j) + u$$

where, $u \equiv \log(v)$. The model is estimated by 'integrating out' the unobservable effect: the distribution of v is specified, for which the parameters can be estimated. Usually the normal distribution of u is assumed for cloglog models. In practice, the survival function is estimated conditional on the error term at its mean value.

So, discrete time nonparametric proportional hazard models with and without unobserved heterogeneity will be built.

In the survival analysis the data structure plays the crucial role. In order to be able to do the survival analysis the following variables should be created:

t – Indicates the time periods the firm is at risk or the length of the spell – number of periods, at which firm experienced negative performance.

y – the binary dependent variable, which is equal to 1 if the firm "died" - had negative performance, when last observed – that is it got into the state and didn't leave it. This variable is often referred to as censoring status. y is equal to 0 if the firm left the state. If the firm leaves the sample having positive performance ("alive") – the data is right censored.

For the firms, which over the observed period experience spells of negative performance several times we have the "repeated spells" or "multi-failure" data. If the spell is not the last – the y will always be 0 as the firm has to get out of it in order to start a new spell.

To account for the repeated spells we have to allow for the inter group correlation, and the groups (firms) be independent. In Stata vce (cluster id) allows to obtain robust variance estimates (Nikolaeva, 2002).

Thus, the right censored, annually grouped continuous time data with repeated spells is obtained.

There will be four models considered, each with different accounting-based performance indicators, which reflect such dimensions of firm's performance as growth and profitability:

- Growth of sales and growth of assets are calculated as the difference of the indicatior in the current period and the previous period divided by the latter.

- Return on assets (ROA) and return on equity (ROE). These are calculated as net income (profit) to assets and equity ratio correspondingly. Net income is taken out of the income statement, and assets and equity values – from the balance sheets of the companies.

For the explanatory variables such firm's characteristics as liquidity, leverage, size, age, and ownership will be included. Also industry and year dummies will be included.

- **Liquidity (WCTA)** – is the indicator of the short-term solvency and reflects the ability of a firm to pay its current operations. In this work the ratio of the working capital to total assets will be used as a measure of liquidity:

$$WCTA = \frac{Working\ \ Capital}{Total\ \ Assets} = \frac{Current\ \ Assets - Current\ \ Liabilitie\,s}{Total\ \ Assets}$$

  Liquidity is believed to have a positive influence on firm's performance. According to Kakani et al (2002) liquidity has time and money dimensions. If a firm is able to free up the recourses, it can fasten the operating cycle, support its investment and growth.

- **Leverage (LEV)** – is an indicator of the capital structure of the company and its solvency. In this work the debt-to-equity ratio will be used to measure it:

$$LEV = \frac{DEBT}{EQUITY}$$

The effect of the leverage on the performance is ambiguous. According to the famous Modigliani and Miller theory the capital structure, that is which financing external (debt) or internal (equity) a firm uses, doesn't influence its value, given the perfect capital markets, no taxes and transaction and bankruptcy costs. However, in real life, these assumptions are not very realistic, and a large body of literature shows that capital structure matters, but the direction of the influence appears to be ambiguous.

The cost of capital differs for the different forms of financing. Retained earnings, debt and equity have progressively higher costs to the firm. In the transition countries the access to the capital is quite limited due to the weakly developed financial markets. The main source of the external capital is bank credit, which is difficult to be got for a long term due to macroeconomic instability. In addition, banks require high collateral, which is not always available.

In general, the influence of the capital depends on the institutions: financial markets development, tax, bankruptcy law, contract enforsment and court system , which is very relevant for the developing and transition countries. (Bevan et al 1999).

- **Size** of the firm is measured as a logarithm of the total assets. On the one hand, size has a positive influence on the performance as larger firms have better access to product, factor and financial markets. They control a big share of the market, they may get better terms of input or financing contracts. On the other hand, as firm gets larger, it becomes more difficult to control and operate (Kakani et al 2002).

- **Age** is age of the firm in the first period of negative performance. Age has a positive effect on firm's performance as it reflects the experience of the firm, its business connections, reputation etc. On the other hand, the opposite effect may be true: younger firms are more flexible. Moreover, in Ukraine as a post Soviet country, high age may mean low efficiency inherited from the past.

- **Ownership** (PRIVAT) is a dummy variable which takes 1 if the firm is private. A lot of literature finds private ownership to have a positive influence on the firm's performance, due to the more effective corporate governance, better controls and absence of the soft budget constrained, which often decrease efficiency (however, the effect may also be opposite). In addition, state-owned firms are often engaged in the non-profit maximizing public activities (e.g. excel labor employment). (Bevan et al 1999)

- **Industry** (IND) – is also important to be controlled for as it captures the concentration effect. In less concentrated industries, the profitability is higher. In addition, we will control for industry specific shocks. Also, there is some control of export orientation (traditionally some industries are more export oriented), which is also an important determinant of the firm's performance. The dummy variables are created by grouping the "kvedcodes" into ten classes (see Table 1 in Appendix).

- **Year** – dummy variables, which control for the macroeconomic shocks and overall business environment in the country.

In this work the data from www.smida.gov.ua is used. The data set includes the financial information of the Ukrainian JSCs (data from the balance sheets and income statement submitted to the state statistical committee) and some general information, such as date of establishment, region, etc. Data for years 1999-2006 are available.

The state registry data set for the ownership information is provided by EROC.

We obtain the panel data set with 32506 observations and with 14243 firms. The estimation procedure requires the panel data with no gaps, so in fact for each model different data set will be used. This data sets will be formed as subsets with the longest spells with no gaps from the general data set, summary statistics of which is provided in the Table 1.

Table 1. Summary statistics of the general data set

Variable	Number of observations	Mean	St. dev.	Min	Max
Dependent variables[2]					
Sales growth	20744	0,31	0,99	-0,99	9,64
Assets growth	21784	0,06	0,32	-0,62	2,37
Return on assets	26096	-0,04	0,10	-0,59	0,26
Return on equity	26096	-0,05	0,34	-2,78	2,03
Independent variables					
Working capital to total assets	35700	0,07	0,28	-1,10	0,90
Debt equity ratio	35699	1,01	3,69	-17,97	42,37
Age	22645	6,01	3,13	0,00	83,00
Size (log(assets))	35700	8,40	1,70	4,00	13,51
Industry	22928	-	-	1	10
Private ownership	36502	-	-	0	1

[2] The firm's performance variables used for creation of the dependant binary variable

Chapter 4

ESTIMATION RESULTS

In this work we will consider four measures of firm's performance, namely, sales and assets growth, return on assets and return on equity. The estimation procedure requires the data with no gaps. For this reason, for each model, the different data sample will be used, which is a sub sample of the original data set, but with the longest spell with no gaps.

As was already stated we have the repeated spell data To account for the repeated spells we have to allow for the inter group correlation, and the groups (firms) be independent. So, we cluster our data.

According to the Jenkin's methodology of the discrete time fully non-parametric PH model estimation we need to create dummy variables to represent the spell length of the negative performance. Since we have different samples, the set of dummies for each model will be different. Since the number of observation for the longer spells is relatively small, the last spells contain several periods.

We estimate the non-frailty (cloglog) and frailty models or model with unobserved heterogeneity (xtcloglog). The estimation results of the non-frailty (cloglog) and frailty model or model with unobserved heterogeneity (xtcloglog) for the growth variables used as the measure of performance are provided in the Table 2. The estimation results of the non-frailty (cloglog) and frailty model or model with unobserved heterogeneity (xtcloglog) for the profitability variables used as the measure of performance are provided in the Table 3.

Table 2. . Estimation results for growth as performance measure models

	Non-frailty (cloglog) models		*Frailty (xtcloglog) models*	
	Sales growth	***Assets growth***	***Sales growth***	***Assets growth***
WCTA	-0.734***	-0.783***	-1.756***	-1.835***
	(0.203)	(0.247)	(0.377)	(0.480)
LEV	0.0251	0.0105	0.0446*	0.0184
	(0.0169)	(0.0211)	(0.0265)	(0.0306)
AGE	-0.168***	-0.144***	-0.391***	-0.325***
	(0.0190)	(0.0291)	(0.0528)	(0.0678)
SIZE	-0.532***	-0.505***	-0.949***	-0.920***
	(0.0211)	(0.0291)	(0.0801)	(0.106)
PRIVATE	-0.204	-0.295	-0.435	-0.548
	(0.217)	(0.334)	(0.318)	(0.456)
D1	2.788***	2.375***	4.630***	3.923***
	(0.0929)	(0.134)	(0.405)	(0.489)
D2	2.894***	2.458***	5.299***	4.481***
	(0.115)	(0.165)	(0.466)	(0.564)
D3	2.392***	2.342***	5.100***	4.965***
	(0.176)	(0.201)	(0.514)	(0.645)
D4[3]	3.096***	2.185***	6.450***	5.481***
	(0.306)	(0.402)	(0.665)	(0.815)
D5[4]	3.673***	-	7.855***	-
	(0.435)	-	(1.016)	-
Industry	controlled	controlled	controlled	controlled
Year	controlled	controlled	controlled	controlled
Observations	5841	3065	7174	3779
Num. of firms			1597	848
SG: Likelihood-ratio test of rho=0: chibar2(01) = 90.74 Prob >= chibar2 = 0.000				
AG:Likelihood-ratio test of rho=0: chibar2(01) = 50.22 Prob >= chibar2 = 0.000				
Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1				

[3] For the sales growth model this dummy represents spell length = 4 years, for the assets growth model this is a spell length > =4 periods (4, 5, 6)

[4] For the sales growth model this dummy represents spell length >=5 periods (5 and 6)

Table 3. Estimation results for profitability as performance measure models

	Non-frailty (cloglog) models		*Frailty (xtcloglog) models*	
	ROA	***ROE***	***ROA***	***ROE***
WCTA	-0.547**	-0.521**	-2.001***	-2.101***
	(0.244)	(0.216)	(0.522)	(0.515)
LEV	-0.00447	0.0259	-0.0125	0.0622*
	(0.0194)	(0.0192)	(0.0318)	(0.0366)
AGE	-0.133***	-0.132***	-0.386***	-0.437***
	(0.0238)	(0.0224)	(0.0730)	(0.0723)
SIZE	-0.496***	-0.495***	-1.243***	-1.281***
	(0.0245)	(0.0230)	(0.111)	(0.101)
PRIVATE	0.00609	-0.199	0.102	-0.433
	(0.224)	(0.216)	(0.391)	(0.395)
D1	2.860***	2.883***	6.634***	6.933***
	(0.127)	(0.121)	(0.669)	(0.640)
D2	2.435***	2.579***	6.791***	7.361***
	(0.143)	(0.135)	(0.677)	(0.652)
D3	2.561***	2.594***	7.249***	7.590***
	(0.160)	(0.157)	(0.696)	(0.668)
D4	2.694***	2.799***	7.573***	8.090***
	(0.185)	(0.184)	(0.715)	(0.697)
D5	1.925***	2.232***	6.975***	7.833***
	(0.373)	(0.359)	(0.832)	(0.811)
D6[5]	1.829***	1.495***	6.905***	6.670***
	(0.419)	(0.464)	(0.836)	(0.815)
Industry	controlled	controlled	controlled	controlled
Year	controlled	controlled	controlled	controlled
Observations	4366	4486	4366	4486
Number of firms			830	855
ROA:Likelihood-ratio test of rho=0: chibar2(01) = 123.43 Prob >= chibar2 = 0.000[6]				
ROE:Likelihood-ratio test of rho=0: chibar2(01) = 125.08 Prob >= chibar2 = 0.000				
Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1				

[5] For both models D6 – dummy for a spell length >=6 periods (6, 7)

[6] The reported 'rho' is the ratio of the heterogeneity variance to one plus the heterogeneity variance. So if the hypothesis that rho is zero cannot be rejected, then frailty is unimportant.(Jenkins, 2004)

Non-frailty vs frailty models

As can be seen from the estimation results the duration dependence is highly significant for all models. Such firm's characteristics as size, age and liquidity (working capital to total assets ratio), are also significant at 1% level of significance (except for the non-frailty profitability models, where it is significant at 5%). Leverage is significant in the models with unobserved heterogeneity for sales growth and return on equity at 10% level of significance. The private ownership is not significant in all four models. According to the results

The likelihood ratio test of the importance of the unobserved heterogeneity is conducted automatically during the frailty model estimation. According to it the unobserved heterogeneity is important in all four models, which is not surprisingly as there are a lot of firm's characteristics that are difficult to account for: corporate governance quality, the political connections, reputation, etc.

As it was expected, the non-frailty and frailty models produce different results. The model without the unobserved heterogeneity underestimates the degree of the positive duration dependence. Also, the other coefficients are higher (less negative) in the non-frailty model. When the unobserved heterogeneity is important, but not accounted for (as in the cloglog models) the biased coefficients are produced. Thus, the frailty model should be estimated.

Baseline hazard

The coefficients near the duration dummies tell us about the shape of a baseline hazard, which represents the duration dependence and is the same for all firms. The firm's characteristics only scale the baseline hazard: it shifts upwards if the certain characteristic increases the probability of failure or downwards - if decreases.

We can see from the estimation results that the shapes of the baseline hazards are different for growth and profitability models. For the sales growth and assets growth models the coefficients are positive and increase with the spell length – which means that we have positive duration dependence – the longer a firm experiences negative performance the higher is the probability that it will not get positive sales or assets growth in the next period. For the return on assets and return on equity models the duration dependence increases up to the 4-year spell length and drops afterwards. So, the probability that the firm's performance will not become positive in the next period increases if the firm has experienced negative performance up to 4 periods. However, if a firm has experienced the negative performance for more than 4 periods, the probability of having a positive performance in the next period increases. The intuition is that the firm cannot experience losses for a too long time. If it got negative profits one year it may be difficult for it to get positive net income in the next period. And this may last for some time. But eventually, the firm either gets profits or disappears.

The differences in the shapes of the baseline hazards could be due to the several reasons. Having positive growth is not crucial for a firm's existence. A firm may have negative growth of assets or sales, and still survive, given that it is able to manage its costs well and operate at least at some profit margin. Moreover, a firm may compensate its decreasing sales with other but operational activities: financial or capital incomes. For many firms assets growth is not a good indicator of performance. For instance, a large wholesaler may buy a large consignment of goods just before the end of the financial year. By this operation it increases its inventory (assets) and accounts payable (liabilities). However, at the beginning of the next financial year, it sells these goods, and decreases its inventory and pays off its supplier.

Firm's characteristics

Estimated coefficients show the proportional effect of the absolute changes in covariates X on the log of hazard ratio. So, in order for the coefficients to be interpreted as hazard ratios, they have to be exponentiated. The following table represents the exponentiated coefficients of the frailty model, which will be discussed.

Table 3. Exponentiated coefficients of firm's characteristics

	Sales growth	***Assets growth***	***ROA***	***ROE***
Liquidity	0.17***	0.16***	0.14***	0.12***
Leverage	1.05*	1.02	0.99	1.06*
Age	0.68***	0.72***	0.68***	0.65***
Size	0.39***	0.40***	0.29***	0.28***
Private ownership	0.65	0.58	1.11	0.65

As can be seen from the table, the coefficients of the significant variables have quite close values in all models.

Liquidity. Liquidity is measured as a working capital to total assets ratio. So, the higher it is, the higher is the short-term solvency of the company. As it was expected liquidity has a positive impact on the firm's performance. One unit increase in liquidity decreases the probability of not exiting the spell of negative performance (failure) by 83% and 84% in the models which use sales and assets growth as a measure of performance and by 86% and 88% in the return on assets and return on equity models correspondingly.

Leverage. Leverage is measured as a debt to equity ratio. The higher is the ratio, the heavier the firm relies on external financing. We find negative (if any) dependence between firm's performance and leverage. It is significant at 10% significance level in the models, which use sales growth and return on equity as measures of performance. So, one unit increase in debt to equity ratio, increases the hazard rate by 5% in the first model and 6% in the second.

Age. The age of a firm in a first period of a spell of negative performance is also very important. One year increase of the age, decreases the hazard rate by 32% and 28% in the models which use sales and assets growth as a measure of performance and by 32% and 35% in the return on assets and return on equity models correspondingly. So, we find positive influence of the age of a firm on its performance. It means that experience, business network, and reputation is important for Ukrainian firms. In addition, we have a relatively "young" samples: the average age of the firms varies from 5 to 7 years, depending on the sample. So, we have not that many old firms, which's flexibility would have suffered from their age. And when the firm is very young, every year of experience is important.

Size. The size of a firm is measured as a natural logarithm of its assets. One unit increase in size, decreases the probability of failure by 61% and 60% in the models which use sales and assets growth as a measure of performance and by 71% and 72% in the return on assets and return on equity models correspondingly. So, we obtained evidence that firms indeed benefit from the large size by obtaining better goods, inputs and financing contracts.

Private ownership is insignificant in all models.

Predicting hazard rates

We proceed with the prediction of the hazard rates using the frailty model (model which takes into the account unobserved heterogeneity of firms).

Following the Jenkin's methodology, we start with predicting $z(t) = \beta' X + D(t) + u$ using the estimated coefficients. Then the hazard rate can be predicted as $h(t) = 1 - \exp(-\exp(z(t)))$. For z(t) we consider a hypothetical firm in 2004, which is private and works in light industry and has the sample average values of liquidity, leverage, age and size.

The Figures 1-4 represent the predicted hazards for such a firm using all four models. As was discussed previously, models, which use growth of sales and assets have an increasing hazard function, whereas models, which use return on assets and return on equity's functions increase up to the 4^{th} period and then decrease. The shapes of the first two graphs also differ: the assets growth hazard increases more monotonically, whereas sales growth graph increase sharply after the third period and decreases slightly before it.

Figure 1. Predicted hazard rate of a hypothetical firm, if sales growth as an indicator of performance is used.

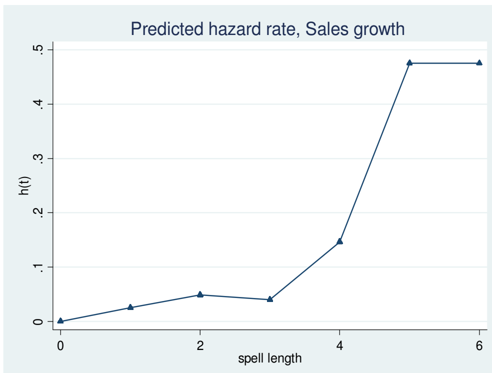


Figure 2. Predicted hazard rate of a hypothetical firm, if assets growth as an indicator of performance is used.

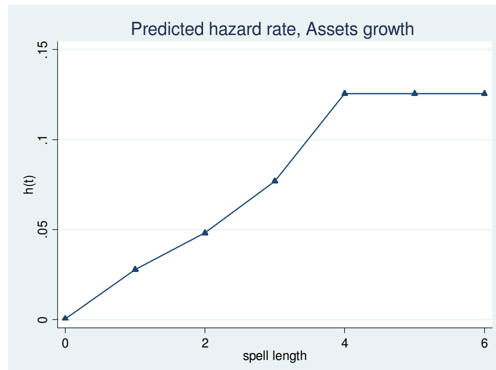


Figure 3. Predicted hazard rate of a hypothetical firm, if return on assets as an indicator of performance is used.

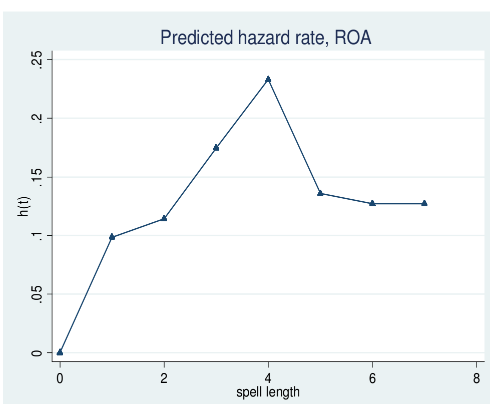
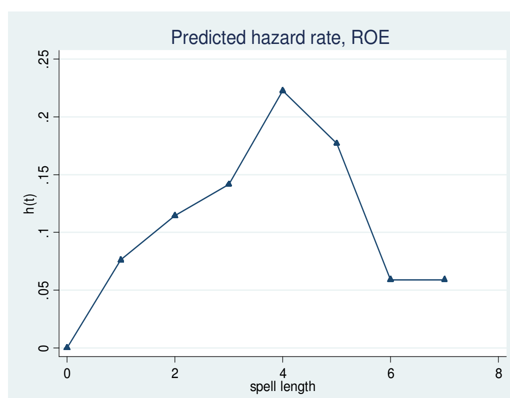


Figure 4. Predicted hazard rate of a hypothetical firm, if return on equity as an indicator of performance is used.



According to the graphs for a hypothetical firm, described above, the first model predicts the probability of failure to be equal 0.15 given the firm experienced negative sales growth for 4 periods. If the firm was having negative assets growth for 4 period, the probability of it to have the negative performance in the next period is 0.13. If the firm had negative ROA for 4 periods the probability to have it negative in the next period also is 0.23. However, if the firm had negative ROA for 5 periods, the probability that it will be negative in the 6^{th} period is 0.14. If the firm had negative ROE for 4 periods the probability to have it negative in the next period also is 0.22. However, if the firm had negative ROE for 5 periods, the probability that it will be negative in the 6^{th} period is 0.18.

Figure 5. Predicted hazard rates of hypothetical firms with different age, performance - sales growth.

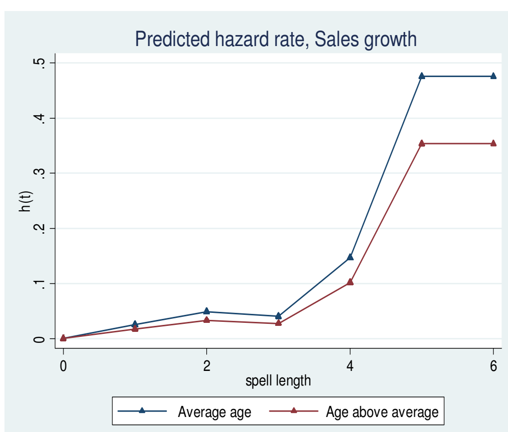
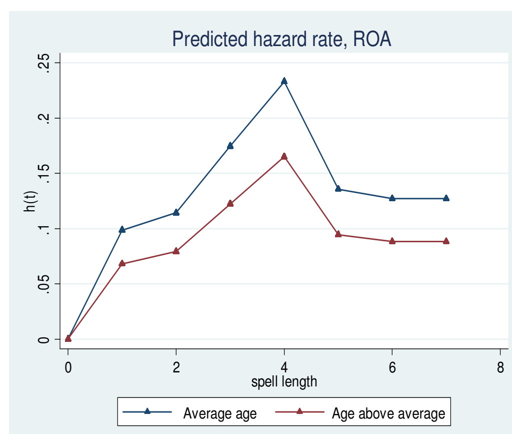


Figure 6. Predicted hazard rates of hypothetical firms with different age, performance - ROA



As it was stated before, the shape of the baseline hazard is the same for all firms, and their characteristics only scale it. On the following figures we illustrate the proportionality of the hazards using the predicted hazard for the same firm as before with the average age and another firm, which is one year older, than average firm. The graphs for sales growth and ROA models are presented in Figures 5 and 6. Graphs for the other two models are presented in the appendix (Figures 1 and 2).

As can be seen from the graphs, even one year of extra experience significantly lowers the hazard of failure. So, indeed the shape of the hazard functions remain the same, but the predicted hazards for the one-year older firm are lower.

The same graphs can be drawn for any of the firm's characteristic.

So, the estimation results show, that duration dependence should be incorporated in the performance analysis. The probability of negative performance was shown to depend on the length of the spell of negative performance. We also find that such firm's characteristics as liquidity, size and age decrease the probability of failure. Levarage has a significant negative influence on the performance in the model with sales growth and return on equity as a performance measures. The private ownership appeared to be insignificant.

Chapter 5

CONCLUSIONS

In this work the firm's negative performance and probability of failure is studied based on the sample of Ukrainian joint stock companies over 1999-2006 years. There are four models proposed to capture the growth and profitability dimensions of firm's performance. We use the discrete non-parametric proportional hazard models to estimate the probability of firm's failure or probability of a firm to have negative performance in the next period, given that its performance was negative several periods before. We show that not only the firm's characteristics matter, but also the length of the spell of negative performance should be taken into the account.

We find the positive duration dependence for the models, in which the sales growth and assets growth were used as performance measures. That is, the longer the firm has negative growth - the higher is the probability of not leaving the spell. However, the hazard of firm's failure increases up to the four-year long spell and decreases afterwards in the models, which use return on assets and return on equity as profitability measures. So, the firm can't experience losses for a very long time: either it eventually makes profits or disappears. The positive growth rates appear to be not that crucial for firm's survival.

Among the firm's characteristics we find liquidity to decrease the hazard rate. One unit increase in liquidity decreases the probability of not exiting the spell of negative performance (failure) by 83% -88% depending on a model. One additional year of age of a firm, decreases the hazard rate by 28-35%. This result supports the idea of the importance of the experience and reputation which are obtained with age. One unit increase in size decreases the hazard rate by 61-72%. So, we obtained evidence that Ukrainian firms indeed benefit from the large size by obtaining better goods, inputs and financing contracts. We also find a negative influence of the leverage on the firm's performance in two models: one unit increase in debt to equity ratio increases the hazard rate by 5-6%.

This work offers another approach to firm's performance analysis. The incorporation of the duration analysis gives the opportunity to make use of additional information, which is ignored, when only the firm's characteristics are considered. However, the duration models are the non-linear models, for which there is no goodness of fit statistics. The endogeneity problems are also not approached with this methodology.

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APPENDIX

Table 1. The industry distribution of a general sample

IND	Industries	Frequency	Percentage
1	Agricultural, mining	3850	17%
2	Light industries	3489	15%
3	Chemistry	1518	7%
4	Metalurgy, metal goods	811	4%
5	Mashinery	2200	10%
6	Electrical, radio, medical equipment, automobile, furniture, recycling, energy, water	1856	8%
7	Constraction	2407	10%
8	Whole sales and retail	2739	12%
9	Hotelling and restaurants, transportation and communication	3132	14%
10	Real estate, rent, informatization, R&D, services for companies, social services(education, medical, etc)	926	4%

Figure 1. Predicted hazard rates of hypothetical firms with different age, performance - assets growth.

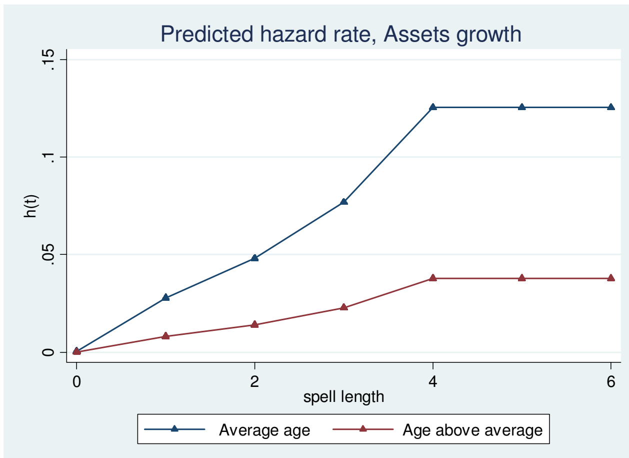

Figure 2. Predicted hazard rates of hypothetical firms with different age, performance – ROE