BANK BANKRUPTCY IN UKRAINE: WHAT ARE THE DETERMINANTS AND CAN BANK FAILURE BE FORECASTED?

by

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Abstract

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The paper examines the causes of bank failures in Ukraine during 1998–2003 using micro-level data. Two basic models are used and their performance compared. The first model is the Giant Logit model, which models the probability of bank failure. The second model focuses on estimating time-to-failure, and uses an Accelerated Failure Time framework with time-varying covariates. In addition to standard financial ratios suggested by the C.A.M.E.L. scheme, I concentrate especially on the role of managerial quality, reflected by DEA efficiency. In this paper, DEA efficiency is preliminarily tested and adjusted for environmental differences. Finally, a bank ranking is built and the forecast for potential failures in July 2003 is made. The results show that inefficient banks tend to fail; so do banks, which over-invest in securities, and hold significant value of demand deposits; bank's size has the opposite effect. Further, an analysis of hazard function shows that for an average bank the probability of bankruptcy increases until the bank reaches the age of approximately 2.5 years, then steadily declines.

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GLOSSARY

AFT. Accelerated Failure Time (AFT) model is an econometric model where the natural logarithm of the survival time is expressed as a linear function of the covariates; the distributional form of the error term determines the regression model

Allocative Efficiency. Allocative efficiency in input selection involves selecting that mix of inputs which produces a given quantity of outputs at minimum costs

Assets. In the accounting sense, all the assets which are or should be of service to an undertaking, valued in accordance with normal accounting conventions

Authorized Capital. The total amount of share capital with which a company has been registered in accordance with its Memorandum of Association. Part of the authorized capital may remain as unissued capital

C.A.M.E.L. Scheme. Bank's situation analysis based on capital, assets, management, earnings, and liquidity examination

Capital. Accumulated wealth or property used in the production of further wealth, i.e. one of the factors of production, the others being land and labour

Data Efficiency Analysis ("DEA"). An econometric non-parametric method which provides measures of relative efficiency among the decision making units, *e.g.* firms.

Demand Deposit. A deposit which is available to the depositor at any time, such as funds in current accounts

Decision Making Unit ("DMU"). – an operating unit under analysis. *see* DEA above

Hryvnya ("UAH"). Official currency of Ukraine. 1 USD = 5.33 UAH[1]

Liability. Insurance guarding against damage or loss that the policyholder, may cause another person in the form of bodily injury or property damage.

[1] January, 2003; Source: Monthly Economic Monitor of Ukraine #2 (28) 2003

National Bank of Ukraine ("NBU"). The central bank of Ukraine, an independent monetary authority of the Ukrainian government

Net Assets. The difference between total assets on the one hand and current liabilities and noncapitalized long-term liabilities on the other hand

Production Frontier. Shows those combinations of outputs which can be produced with fixed amounts of inputs conditional on the inputs being employed efficiently.

Savings Deposit. A bank or building society account where money can be deposited regularly and which pays interest, often at a higher rate than a demand deposit account

Technical Efficiency. Measures actual underuse of inputs relative to their maximum potential.

Time Deposit. Money invested for a fixed predetermined period at a higher rate of interest

Chapter 1

INTRODUCTION

From year to year, strong attention has been paid to the study of the banking sector and, particularly, the problems of predicting and preventing bank's bankruptcy. Why? The answer is straightforward: the banking system, acting as a channel of funds between lenders and borrowers with productive investment opportunities, is an essential part of a healthy economy. Banks are the most important of financial intermediaries, without which the economy cannot function smoothly and efficiently.

The paper considers soundness as an important characteristic of bank industry performance and, hence, its ability to ensure economic growth. Recent research has found that an important reason why many developing or ex-communist countries "*experience very low growth rates is that their financial systems are underdeveloped*" (Roubini and Sala-i-Martin (1995)). Thus, an efficiently functioning banking system stimulates economic growth through channeling funds from savings to investments, and secondly, strengthens people's credibility, which leads to the possibility to stabilize the economy. This is extremely important to the developing economies. As noted by Bonin *et al* (1998), the major characteristics of most developing countries are the lack of confidence in the financial system stemming from historically unstable macroeconomic environment, frequent high inflation, and a high degree of bad loan creation and the susceptibility of banks to the impact of external shocks. Under such conditions, the individual bank's failure may result in a system-wide panic, which causes depositors to withdraw their deposits from other banks until the banks fail. The liquidation of a large number of banks in a short period of time causes strong reduction in economic activity (Mishkin and Eakins (1999)).

How important is the banking sector for Ukrainian economic development and how well does it perform? The share of population who trust the Ukrainian banking system has increased (Tshvediani (2002)). For example, total banks' deposits grew from about 5.36 billion UAH (about 1.73 billion USD) at the beginning of 1999 to more than 25 billion UAH (about 4.82 billion USD) in 2002[2]. Despite the certain improvements, its functioning as an efficient financial intermediary is still extremely limited. The percentage of problematic banks by 2000 was 32% of all banks operating in Ukraine. Their number grew significantly after the 1998 crisis, from 10 in 1997 to 52 in 1999, and to 72 in 2000 (Popryga (2001)). The amount of new deposits reached 7 bln UAH in 2002, which is 3.2% of GDP (MEMU (3/2003)). Compared to other transition economies of Central Europe, these amounts are clearly less. For example, new deposits in Estonia and Hungary in 2000 were equal to 10 and 7% of their GDP's, respectively (Roe (2000)). Thus, the National Bank of Ukraine (NBU), which is primarily aimed at controlling banking sector, setting rules and regulations to keep the sector stable and efficient, should be interested in improving Ukrainian banking sector performance.

Identifying the causes of such a moderate performance of the banking sector in Ukraine is the first step toward improving the situation. The banking sector performance is preconditioned by various economic, legislative, regulatory and political factors.

One of the impediments to the efficient functioning of banking sector is poorly developed legal system, and particularly, the lack of clear, transparent government

[2] Estimates; based on the data available

policies toward bank failures. This is apparent in the observation that the bankruptcy procedure is very slow and cumbersome. For example, the process of liquidation and repayments of the debts of "Slov'yanskyy" bank[3] lasted more than one and a half years[4]. During this time more than its 70 depositors have died from nervous stress, heart attack, etc. (Liga Online, August (2001)).

In addition, "*banks do not operate in competitive environment, since the government stands ready to bail out many of them*" (Popruga (2001)). There is a portion of the so-called "pocket banks" that are established with a mission incompatible with market goals. These are "*created for the purpose of obtaining cheap central bank finance for the companies, the parties or the ministries, which established them*" (Bonin, Mizsei, and Szekely (1998)). That is why political reasons may also cause some banks to become bankrupt and some others to perform better.

Besides, the presence of foreign banks in Ukraine is very low: only 6 completely foreign-owned banks operate in the local market (as for Jan, 2003). Undoubtedly, this significantly decreases competition significantly. Under these conditions, banks can hardly operate efficiently generating sizeable and stable profits.

The main goal of this paper is the estimation of economic determinants of bank failures in Ukraine during 1998–2003 using micro-level data. The analysis is based on the two models: the first estimates the probability of a bank failure and the second estimates the time-to-failure. In addition to standard financial ratios, the major concern is on the role of managerial quality, which seems to influence bank's performance significantly and may be reflected by DEA efficiency. To

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[3] "Slov'yanskyy" bank was one of the top banks in terms of its performance in 2000. Official date of failure – July, 17 2000 (Polischuk (2002))

[4] Its important to note that in the recent past there was no deposit insurance system in Ukraine. However, on the 28th of August, 2002 the Ministry passed a law on creation of the Deposit Insurance Fund. Its functioning is still limited however as it repays only the deposits, which are less than 1500 UAH (about 300 USD) – quite a low value even for Ukraine (Rudenko (2002)).

take into account environmental differences, estimated efficiencies were adjusted for environmental heterogeneity.

The results show that inefficient banks tend to fail; so do banks, which over-invest into securities, and hold significant value of demand deposits. Bank's size has an opposite effect. Further, an analysis of hazard function shows that for an average bank the probability of bankruptcy increases until the bank reaches the age of approximately 2.5 years, then steadily declines.

This work is arranged as follows. The next section presents a literature review and discusses previous work done on the topic in the world and Ukraine in particular. It also describes the data set used. Chapter 3 considers the concept of efficiency and methodology used to measure it, as well as presents results of the measurement. Chapter 4 describes theoretical issues concerning the variety of econometric models applicable in our case, and provides comparative estimation by both multiperiod logit and hazard models. Testing for robustness, discussion of the results, and possible policy implication follow.

Chapter 2

LITERATURE REVIEW

Economists and financial analysts have been analyzing the determinants of bankruptcy for decades (*see* Altman (1993) for a survey). The first research on this issue (*e.g.*: Hardy and Meech (1925)) go back to the famous US banking sector crisis in 1920-1930s, and were primarily statistical. By using simple Analysis of Variance (ANOVA) techniques the authors were attempting to answer the question as to whether *"failed banks exhibit significantly different ratio of measurements than continuing entities"* (Altman (1968)). As noted by Hardu and Virág (1990), the first researcher who used an indicator-based (*i.e.* based on various constructed indicators, for example – financial ratios) approach for prediction purposes was Beaver in 1966.

However, it was not until the seminal work of Altman (1968) that research as to the determinants of bank failures moved towards quantitative measurement. As was pointed out by Popryga (2001), by applying linear discriminator analysis (DA)[5] Altman was the first who gave a quantitative answer to the question *"which factors are most important in detecting bankruptcy potential, what weights should be attached to those selected ratios, and how should the weights be objectively established"* (Altman (1968)). He found that the discriminant function was accurate not only within the sample, predicting bankruptcy correctly in 94 percent cases, but also in several secondary (testing) samples. However, Shumway (2001) tested Altman's variables out of sample and came to much poorer results: among the banks in top 30% ranked by their probability to fail, only 67% of banks actually failed.

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[5] Linear discriminating analysis is "*a statistical technique used to classify an observation into one of several a-priory groupings dependent upon the observation's individual characteristics"* (Altman (1968)).

Moreover, the use of DA is limited by the fact that "*there exist an excessive number of strict assumptions that limit the scope of investigation [using discriminant analysis (DA)]*" (Ohlson (1980)); one of the most restrictive among them is requirement to draw a match sample, and thus, to have huge number of observations, which is quite problematic in transition economies.

The next step in the development of failure prediction was achieved after the development of the dichotomous dependent variable estimation theory, and the logit-probit methodology, which is much less restrictive, and thus – more suitable. Hajdu and Virág (1990) mentioned that logistic regression *"is clearly an alternative to discriminant analysis"*. Santomero and Vinso (1977) were the first, who introduced these stochastic models with respect to banks failure analysis. And from that time, probabilistic modeling became a prevailing technique – according to Shumway (2001) even nowadays most researchers use them. For the recent examples, one could refer to Zvijevski (1984), Wilson (1992), and Popryga (2001). All of them (among many others) tried to find a significant dependence of the financial system on various its characteristics, as well as on the macroeconomic environment. Hajdu and Virág (1990) contains summary results of selected bankruptcy studies, dated from 1968 up to 1990, which indicate that logit (probit) modeling leads to relatively good results. Accuracy of classification ranged from 76% in the work of Zmijewski (1984), where he employed probit and weighted exogenous sample likelihood model (WESML) to investigate firms listed on the American and NYS Exchanges from 1972 to 1978, which have SIC industry code less than 6000, to 96% in the study by Pantalone and Platt (1987), where the authors use logit analysis to determine the causes of banks bankruptcy in US after the deregulation. Hajdu and Virág (1990) applied both discriminant analysis and logit estimation to the sample of Hungarian banks, and show superiority of the latter: while DA gives on average only 57% of correct predictions (*i.e.* bankrupt banks as bankrupt, and sound ones as sound), logit improves this result to 63%. As the dependent variables, the authors use various accounting ratios, taking in one period, and thus limit themselves by using cross-section, rather than pooled data, which probably is superior. Popryga (2001) states that the pooled time-series limited dependent variable model estimation is the most common technique in investigating banks failure. Shumway (2001) supports her point of view, and says that *"most [previous] researchers estimated single-period models … with multiple period bankruptcy data"*. As far as I know, there is only one work on prediction of failure of Ukrainian banks – Popryga (2001) – which falls exactly into this category of models. In this work, the author investigates the causes of banks bankruptcy in Ukraine based mainly on financial ratios of 111 Ukrainian banks calculated for the years 1995 and 1996. The main result is that traditional indicators (like, for example, return on equity) do not play a significant role in the soundness of Ukrainian banks; however, soundness does depend on the location of the bank and the number of years in business.

There is a variety of reasons for this undoubtly popularity of logit estimation. First, these models seem to be superior relative to other alternatives, such as duration models, when the economic environment is highly unstable, and bankruptcy arises from non-economic[6]. Secondly, the limited dependent variable model is more stable to omitted variable bias than, for example, the above-mentioned duration models, and does not require long panels for obtaining robust results (Kennedy (1999)). Therefore, logit can be a good choice when there is a lack of data, which is typically the case in transition economies (Canhoto and Dermine (2000), Hanousek and Roland (2001)). Logit analysis provides answers to a number of questions, which traditional indicator analysis failed to answer, like which indicators are the most important and how to objectively select such indicators (Hardu and Vigár (1990)).

[6] Thanks to prof. Peter Kennedy for this suggestion

However, all the above-described models have several huge drawbacks. The main one is conceptual – probit models concentrate purely on the probability of failure, and disregard the timing of failure (Borovikova (2000)). This leads to undesirable effect: "*by ignoring the fact that firms change through time, static models produce … biased and inconsistent estimates of the [bankruptcy] probabilities. Test statistics that are biased on static models give incorrect inferences*" (Shumway (2001); this work contains detailed proof of this fact). Another problem of static models is that the researcher chooses arbitrarily when to observe the bank's characteristics: *"Most forecasters choose to observe each bankrupt firm's data in the year before bankruptcy"* (Shumway (2001)). All these are potential reasons for the increased use of the duration modeling, which allows to predict a bank's survival time, given the bank's characteristics. There methods, generally applied in medical studies, permit considerable adoptability. They proved to be useful in the analysis of marriage duration, time between sons birth, wars, jobs duration, etc. Technical details also allows flexibility. Some of the authors (Dabos and Escudero (2000)) use proportional Cox (1972) model with static covariates (partially ignoring the dynamics) – by Bercoff *et al* (2002), this approach was the most common in the nearest past. While the others (Wilson and Wheelock (2000), Shumway (2001)) allow for time-varying covariates. Models used also differ in either parametric (*e.g.* log-logistic baseline hazard) or non-parametric (*e.g.* proportional hazard) method is used: while the former allows making additional inference about the dependence of the probability to fail in time, the latter is far less restrictive. Cole and Grunther (1995) and Borovikova (2000) suggest using a split-population survival model, which allows to split determinants on those of failure and that of timing of failure. However, this approach requires running a separate (hazard) regression over the sample of failed banks, which in its turn requires a relatively big number of them. An interesting fact is that many researchers that use duration analysis point out that "*about a half of the accounting ratios that have been used to forecast bankruptcy are not statistically related to failure*" (Shumway (2001)).

While much of the above discussed research use various financial ratios and bank's characteristics as explanatory variables, some authors advocate concentration on *managerial quality as an alternative* as this is the most valuable characteristic of a bank. This alternative view is further supported by the opinion that *"financial ratios do not capture long-term performance"* (Sherman and Gold (1985)). Schaffnit *et al* (1997) add that *"ratios give only a one dimensional, incomplete picture"*. Thus, there exist another branch of the research that bases its conclusions on estimating of the *efficiency* of a bank. Berger and DeYoung (1997) by employing Granger causality test. This research found that measured cost efficiency precedes reduction in problem loans, and reduction in capital precedes increases in problem loans. Hence, cost efficiency may be an important indicator of problem banks. Indeed, analyzing US banking sector from 1984(3) to 1993(4), Wheelock and Wilson (2000) found that "*apart from excessive risk-taking, or simply bad luck, banks that are poorly managed are thought to be prone to failure"*. Berger and Humphrey (1992) bolster them either. Berger and DeYoung (1997) also provide support to this claim by indicating that *"failing banks tend to be located far from the best practice [efficiency] frontier"*. Therefore, another popular method of banks' sector analysis is the efficiency estimation.

The methodology I choose to measure productive efficiency is Data Efficiency Analysis (DEA) since *"recent research has suggested that the kind of mathematical programming procedure used by DEA for efficient frontier estimation is comparatively robust"* (Seiford, Thrall (1990)). Efficiency analysis is not limited to bankruptcy forecasting only, its scope is very broad. Sathye (undated) using DEA investigates the productive efficiency of public, private, and foreign owned banks, and makes suggestions on possible policy implications. Canhoto and Dermine (2000) concentrate on comparing the efficiencies of new and mature Portugal banks, and conclude that deregulation occurred in Portugal in the mid-1980 was beneficial to its banking system. Jemrić and Vujčić (2001) came to similar conclusions analyzing Croatian banking system: new and foreign banks appeared to be more efficient than old ones.

Limited dependent variable estimation, duration models, and prediction of failure through calculating efficiency typically are not 'overlapped' – most of the authors choose only one of these approaches. However, the most recent research (*e.g.* Wheelock and Wilson (2000)) managed to combine them. The authors, as the first step in applying efficiency analysis, estimate managerial efficiency. In the second step they use duration analysis, where managerial efficiency serves as one of the explanatory variables, which appear to be highly econometrically significant.

Therefore, in my thesis I will follow the most recent tendency, and will first, estimate Ukrainian banks' productive efficiency. Secondly, I will use this variable, as well as other explanatory variables, to compare both logit and hazard models in order to choose the model for that more accurately identify the factors causing banking failures in Ukraine. The models will be evaluated based on their ability to predict failure.

Chapter 3

DATA DESCRIPTION

The data used were collected primarily from two sources. The first source is "Business" journal, which periodically publishes the data on banks and banking sector collected by Ukrainian Banks Association. The second source is "NBU Herald" journal, which is an independent data collector, and uses the information submitted by banks to the National Bank of Ukraine[7]. The data set covers the period from 1998 to 2003, and consist of 2 observations per each year; typically in January and July.

The main dataset includes the following indicators on a bank-by-bank basis[8]:

i. *Assets and Liabilities*. This column includes data on both net and total assets and liabilities. Net assets are derived from total assets after subtraction of "technical bank accounts", e.g. inter-branch turnover, and thus represent real amount of money bank operates. This concept closely relates to what is known current assets. Net liabilities are nominal money balances, which a bank owes to its depositors, creditors, etc.

ii. *Deposits*. This section includes statistics on the total value of individual and business deposit accounts in a bank. The data includes also a subdivision into demand deposits (available at any time) and time and savings deposits (deposits where money invested for a fixed period and

[7] As far as I know, this data is the only one official data available in Ukraine.

[8] Explanations of various terms used by Ukrainian Banks Association (which may differ from common practice) are taken from comments of Tyampa (2001) and "Campbell Finance Glossary".

deposits, where money can be deposited regularly and which pays interest, respectively)

iii. *Capital and Profits*. Include fixed capital, authorized capital, and net year profits (forecasted for the entire year given the profits of the last period). Reported profits are calculated after assignments to bank's reserves and thus, are understated[9].

iv. *Credit-Investment Portfolio (CIP).* The data includes total amount kept in various financial instruments and loans; with subdivision into interbank loans, consumer loans, commercial and industrial loans, and investment into securities.

All the data is measured in nominal terms. In addition, the CPI index, taken from MEMU #2 (Feb.) 2003, is used to correct for inflation.

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[9] I need to mention that Neyelov (2001) notes that "Profits" value cannot be considered as a good indicator of bank's earnings – "*no one knows how much earning the bank spent to form reserves, what share of reported profits are future discounted profits, etc [translated by the author]*" he states. Tyampa (2001) add that sometimes banks underreport their profits to pay less taxes; on the other hand, they may overstate profits not to show their unprofitableness

Table 1 Data summary

Date	1.1999	7.1999	1.2000	7.2000	1.2001	7.2001	1.2002	7.2002	1.2003
Total # Banks	130	129	131	122	127	128	130	126	135
# Failed	11	7	9	10	3	5	8	7	-
# DeNovo (New)	-	12	4	6	12	5	4	1	1
All banks									
Net Assets	29.27	44.02	49.88	71.24	83.17	97.16	109.28	138.09	154.91
Net Liabilities	16.71	28.49	28.30	48.78	56.67	68.01	75.94	94.02	115.93
Individual Deposits	1.61	3.09	4.52	8.02	8.47	12.32	14.42	22.10	32.03
Business Deposits	6.09	9.34	10.50	20.04	22.43	26.26	28.46	35.98	44.95
Capital	9.92	12.47	17.44	21.64	27.34	28.30	29.58	31.77	32.68
Profits	0.92	0.37	1.17	0.44	1.02	0.50	1.04	0.47	1.17
CIP	16.81	20.64	24.00	35.79	51.90	63.47	76.13	99.42	114.56
Non-failed Banks									
Net Assets	31.21	44.02	51.31	73.32	83.91	98.59	112.39	138.50	-
Net Liabilities	18.28	28.57	28.68	49.80	56.69	69.91	80.67	94.06	-
Individual Deposits	1.65	3.20	4.75	7.73	8.53	13.10	15.07	23.04	-
Business Deposits	6.42	9.74	10.62	19.35	22.54	28.64	32.58	36.59	-
Capital	10.14	12.47	17.36	22.69	27.38	28.75	30.79	31.94	-
Profits	1.10	0.37	1.18	0.47	1.03	0.51	1.20	0.47	-
CIP	17.61	20.64	24.34	37.32	51.99	64.94	77.26	100.30	-
Failed Banks									
Net Assets	7.87	44.16	36.33	35.37	63.22	27.49	54.86	68.62	-
Net Liabilities	3.71	23.16	17.18	15.03	27.81	10.55	33.79	43.24	-
Individual Deposits	0.61	0.61	1.38	8.48	1.40	0.03	6.81	0.86	-
Business Deposits	2.34	5.89	5.49	27.43	8.03	1.46	8.58	3.38	-
Capital	3.77	13.35	19.10	16.61	22.53	23.48	26.28	30.58	-
Profits	0.07	0.04	1.00	0.16	0.11	0.05	0.80	0.68	-
CIP	4.08	16.49	22.54	20.63	29.15	20.95	44.23	69.18	-

Note: all financial variables are measured in current millions of hryvnya. Median values are reported. Standard deviations are typically 10 times the median. Full dataset is available upon request.

Unfortunately, not all of the Ukrainian banks are members of the Ukrainian Banks Association (typically, about 130 out of 150 banks enter UBA), and therefore, we have to accept some selection bias. Secondly, those banks which are not members of the UBA, typically were created by and for some big companies to serve their needs (only), and therefore, cannot be considered as a real part of banking system in Ukraine: they typically do not publish their data, not really interested in attracting outer deposits. By Budkin (2000), because of the fact that these banks depends mainly on their major stockholder, and cannot survive in case of its bankruptcy, the probability to fail of these banks is above average.

C h a p t e r 4

THE MEASUREMENT OF PRODUCTIVE EFFICIENCY

Overview

Measuring managerial efficiency is highly important, because it influences the overall performance of the bank, and its probability to fail, as was found by the great number of research. Thus, finding the efficiency of Ukrainian banks is a valuable part of my paper.

To begin with efficiency, let me first start with a closely related concept – productivity. Based on Coelli *et al* (2002), *productivity* is the ratio of the output(s) that a firm produces to the input(s) that it uses. The *production frontier* represents the maximum output attainable from each input set. Hence, a firm operates on that frontier is called *technically efficient*, and beneath the frontier – *technically inefficient*. Therefore, generally, *"efficiency … measures how much more output could be produced from the same inputs, or how much less input could be used to produce the same output"* (Wheelock and Wilson (1995)).

As noted by Chen (2001), the overall bank efficiency can be decomposed into scale efficiency, scope efficiency, pure technical efficiency, and allocative efficiency, i.e. for a bank to be considered "efficient" is must simultaneous achieve the four types of efficiencies.

The banks have *scale* efficiency when they operate near the constant return to scale range, and thus, cannot gain through increase or decrease their production. It is worth talking about *scope* efficiency when a bank is diversified into (efficient) number of various branches, offering right mix of services. But the most popular and widely used efficiency measures in the banking industry (Wheelock and Wilson (1995), Wheelock and Wilson (2000), Aly (1990), Berger and DeYoung(1997), etc.) seems to be *technical* and *allocative* efficiencies, which both refer to managerial efficiency. *"Allocative efficiency measures errors in choosing an input mix that is consistent with relative prices"* (Chen (2001)), while technical inefficiency indicates overuse of inputs. It is worth mentioning that allocative efficiency and technological efficiency frequently led to very different estimates (*see* e.g., Ferrier and Lovell (1990)). By Färe and Primont (1995), *overall efficiency* can be defined as a product of technical and allocative efficiencies. Because allocative efficiency requires knowledge of the price vector of inputs, and because of lack of data on it, I am unable to estimate allocative efficiency. Therefore, in this work I will estimate technical efficiency only, which will overstate overall efficiency (both efficiencies are bounded by 0 and 1), but for sure can serve to characterize the management quality of all the banks in the dataset.

Data Envelopment Analysis

i. Introduction to the Data Efficiency Analysis (DEA)

There are various techniques used to estimate efficiency; however, all of them require some knowledge of technology. As noted by Zelenyuk (2002), there are basically 4 groups of methods generally applied to estimate efficiency, which can be represented in the following table:

Table 2 The principal techniques for efficiency estimation

	Non-Parametric	Parametric
Non-Stochastic	DEA	Linear programming estimation

Stochastic	DEA with bootstrapping	Stochastic Frontier Analysis (SFA)

All the methods differ in underlying assumptions. Parametric and non-parametric ones distinguish in either assuming some functional form of technological function or not. Stochastic and non-stochastic differ in that the former allows for fluctuations, while the latter does not.

To measure efficiency, I use Data Envelopment Analysis (DEA). *"Data Envelopment Analysis is a methodology for analyzing the relative efficiency and managerial performance of productive (or response) units, having the same multiple inputs and multiple outputs"* (Jemrić and Vujčić (2001)). DEA, occasionally called frontier analysis, was firstly introduced by Charnes, Cooper and Rhodes in 1978 (Anderson (undated))[10]; Sherman and Gold (1985) were the first who applied DEA to banking (Sathye (2000)). Briefly, this methodology divides all the players into the best ones, i.e. the most efficient, which are situated on efficiency frontier, and less efficient, which are inside the set bounded by the frontier, and the inefficiency of the latter is measured by the distance to the frontier. I used one of the major and popular DEA model (Jemrić and Vujčić (2001)) named CRS ratio model (constant return to scale).

As every method, DEA has both strengths and limitations. Based on Anderson (1996), Chen (2001), Färe and Primont (1995), and Wheelock and Wilson (2000), the main strengths of the method are:

[10] Most of examples below are also based on Anderson (1996)

1. Non-parametric form. DEA does not require any parametric form of, say, production or cost function, which possibly imposes any, sometimes – unrealistic assumptions.
2. Different inputs and outputs may have different units of measurement. For example, one input may be measured in the number of staff members, while another input, e.g. total loans value, can be measured in dollar amount.
3. All producers can be easily compared to each other, because DEA returns a single index – the efficiency of Decision Making Unit (DMU), which can be easily compared with that of other units.

And the weaknesses of the DEA approach include:

1. No random fluctuations are allowed, i.e. no measurement error. This means that every deviation from the frontier is treated as inefficiency.
2. DEA does not take into account input prices, but only input amounts. So, it ignores allocative efficiency.
3. Impossibility of hypothesis testing, i.e. (pure) DEA returns only estimates, without standard errors.

Nevertheless, despite the weaknesses, DEA analysis is appropriate because of numerous strengths of the approach and limitations of the data available.

ii. Efficiency Estimation using DEA

As I mentioned, this method can be used to evaluate the relative technical efficiency of DMU. To proceed further, I need some definitions:

$$\text{Technology } T = \{(x,y): x \text{ can produce } y\} \tag{1}$$

$$\text{Technology}^{11}\ \hat{T}_{CRS} = \{(\vec{x},\vec{y}): \vec{Y}\vec{z} \geq \vec{y}, \vec{X}\vec{z} \leq \vec{x}, \vec{z} \geq 0\} \tag{2}$$

$$\text{Input Correspondence } L: \Re_{+}^{m} \Rightarrow \{\vec{x}: (\vec{x},\vec{y}) \in T\} \tag{3}$$

$$\text{Output Correspondence } P: \Re_{+}^{m} \Rightarrow \{\vec{y}: (\vec{x},\vec{y}) \in T\} \tag{4}$$

where X and Y are matrices of inputs and outputs. Non-increasing returns to scale technology, non-decreasing returns to scale, and variable returns to scale technologies require in addition $\sum z \leq 1$, $\sum z \geq 1$, and $\sum z = 1$, respectively. In terms of the above defined concepts, output distance function D_o is defined as:

$$D_o(x,y) \equiv \inf\left\{\theta > 0 : (x, \frac{y}{\theta}) \in T\right\} \tag{5}$$

$$D_o^j(x,y) \equiv \max\left\{\theta_j > 0 : (x_j, \frac{y_j}{\theta_j}) \in \hat{T}\right\} \tag{6}$$

The input distance function D_i is defined in similar way. The choice between input- and output-oriented distance functions is determined by the nature of the problem. For example, state companies (e.g. STATEENERGO - electricity company) have to produce a more-or-less fixed output, and their goal is to contract inputs as much as possible. These firms are called *cost minimizing*. Hence, in this case it may be better to use input oriented distance function. Firms which aim is to produce as much as possible given fixed inputs are *revenue maximizing*, and usage of output-oriented distance function is preferable. In the long-run, firms are both revenue maximizing and cost minimizing, i.e. *profit maximizing*, and therefore, both input and output approaches work. I assume that banks are profit maximizing.

Therefore, in case of one input and one output, efficiency is measured just by taking the ratio of output to input, and then – calculating *relative efficiency* with respect to the most efficient DMU. In two outputs-one input case (*e.g.:* deposits are used to produce both loans and investments into securities), the picture becomes as following:

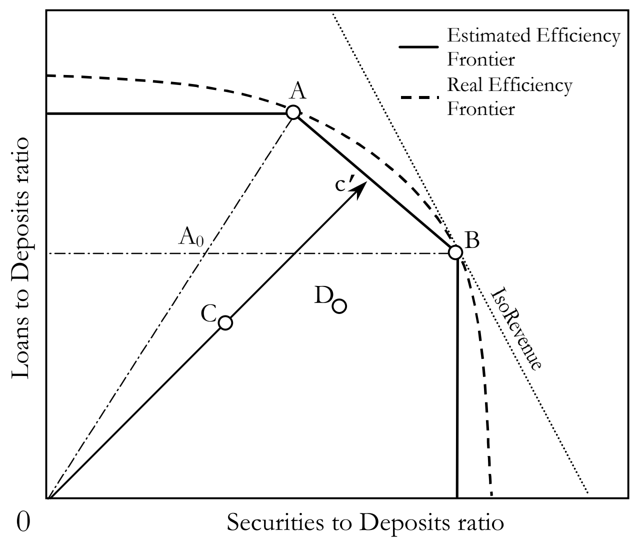

Figure 1 The concept of efficiency

Here, {A, B, C, D} are DMU's. A and B are on the *efficiency frontier*, and therefore, can be treated as efficient ones with efficiency equals 1. C and D are inefficient, and efficiency in case of C can be calculated as the ratio of (0C) to (0c′)[12]. For unit C frontier point c′ can be viewed as a target, which can be achieved either by setting *input targets* – those which deal with inputs or *output targets* – which deal with outputs. So, to achieve efficiency frontier, both C and D can:

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[11] By this technology set I mean estimated technological set. Also some additional restrictions were assumed, such as free disposability, additivity, etc.

[12] It is clear that to use this methodology I have to assume that technological set has to be convex. The intuition can be the fact that we always can build some hypothetical DMU which is a linear combination of those, lying on the frontier.

1. Reduce inputs
2. Increase both outputs while keeping inputs constant
3. Do combination of the above

In multi-input – multi-output case this problem takes the following form. We have J decision making units, each of them transforms set of inputs $X_j = \{x_j^n\}, n = \overrightarrow{1,N}$ into set of outputs $Y_j = \{y_j^m\}, m = \overrightarrow{1,M}$, and $j = \overrightarrow{1,J}$. Therefore, for each DMU we get an optimization problem:

max Ej: s.t.c[13]*.:*

$$
\begin{aligned}
&E_k = \frac{x_k^n w_n}{y_k^m v_m}, k = \overrightarrow{1,J} \\
&E_k \in [0;1], k = \overrightarrow{1,J} \\
&v_n, w_m \geq 0, n = \overrightarrow{1,N}, m = \overrightarrow{1,M}
\end{aligned}
\tag{7}
$$

$$j = \overrightarrow{1,J}$$

where E denotes efficiency, and v, w – weights of corresponding factors (inputs and outputs), which are chosen so that to maximize efficiency. Fortunately, this model can be easily simplified. For this purpose, I followed a Charnes-Cooper transformation (Jemrić and Vujčić (2001)), and choose a representative solution *(v; w)* for which the denominator $y_j^m v_m = 1$[14]. So, the objective function transforms into a simple linear one. And the solution will straightforwardly collapse to the value of efficiency.

Andersen and Petersen (1993) introduced a modified concept of efficiency - *superefficiency*, which intuition is as following. It is seen from *Figure 1* that DMU "A" is efficient, and therefore, its efficiency equals 1. However, if we consider a

[13] Here and below upper and lower indexes denote summation.

DMU which can be characterized by point A_0 (strictly speaking, slightly above A_0) instead of that by A, it will still remain efficient with efficiency equals 1. And therefore, the formal definition of efficiency does not take this case into consideration. To improve this, they suggest to leave standard definition of efficiency for non-efficient units, but to restate it for efficient ones. For efficient DMUs a score now *"indicates the maximal radial change which is feasible such that the DMU remains efficient"* (Scheel (2000)). In our case, superefficiency equals the ratio of (0A) to ($0A_0$); hence, in case of efficient units, superefficiency will be more or equal 1. Technically, superefficiency is estimated in the way usual efficiency is, but without inclusion of DMU under consideration into the constraint $E_k \in [0; 1]$ on bounded efficiency (*Equation 7*).

Calculation of scale efficiency is based on the following. Let A-H on *Figure 2* are decision making units, and all they transform input into output.

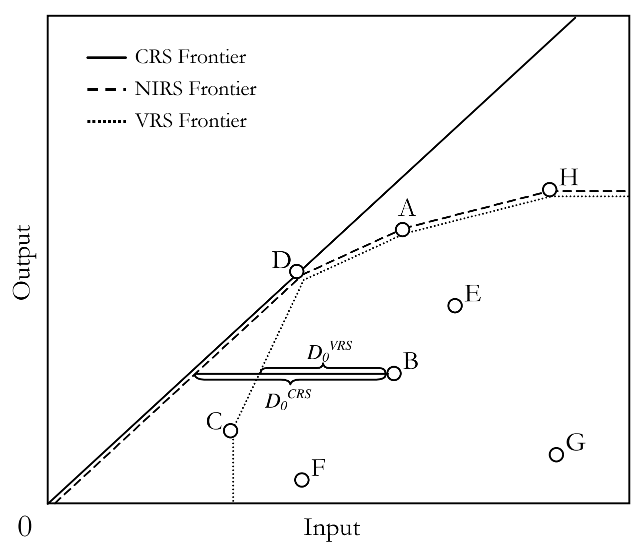

Figure 2 Measure of the efficiency under
CRS, NIRS, and VRS assumptions

[14] Linear programming problem obtained after this normalization of inputs is called "input-oriented CRS model"

Based on the assumptions on technological set, it will have either non-increasing (NIRS) or non-decreasing (NDRS) or variable (VRS) or constant (CRS) returns to scale. Scale efficiency (SE) can be calculated as the ratio of VRS technical efficiency (D^{VRS}) to CRS technical efficiency (D^{CRS}). In case of input (output) technical efficiencies, scale inefficiency will be in inputs (outputs). DMU is scale efficient if its scale efficiency is equal 1, i.e. VRS technical efficiency equals CRS one (DMU "D" on the *Figure 2*). DMUs above the tangency point ("D" in our case) are "too big" – they may decrease their size to achieve higher scale efficiency; those, which are below tangency point are too small and can gain from increasing their size (e.g. inputs). However, in both cases scale inefficiency gives the same results – it is smaller than 1. To distinguish increasing and decreasing returns to scale range, it is possible to define SE^* as following:

$$SE^* = \begin{cases} \dfrac{D^{vrs}}{D^{crs}}, D^{vrs} = D^{nirs} \\ \dfrac{D^{crs}}{D^{vrs}}, D^{vrs} \neq D^{nirs} \end{cases} \tag{8}$$

which guarantees that for the increasing returns to scale range ES^* will lie between 0 and 1, and for decreasing returns range – between 1 and ∞[15].

Implementation and the Results

i. Specifying inputs-outputs sets

To measure technical efficiency and imply DEA, one must specify the inputs and outputs being taking into account. Because the banks use a number of inputs to

[15] Next, various software can be used to perform calculations, for example: Warwick DEA software, Frontier Analyst – marketed by Banxia Software, DEAP, and others (*see* Coelli (1997) *et al.* for description of some of them). In this work, I used EMP 1.3.0 software for making mathematical calculations. This software is provided for free for academic use and can be downloaded from the web-site http://www.wiso.uni-dortmund.de/lsfg/or/scheel/ems/

produce thousands of outputs, the model has to be simplified. Basically, *"the choice of inputs and outputs in DEA is a matter of long standing debate among researchers"* (Sathye (2000)). Jemrić and Vujčić (2001) suggests the use of fixed assets, number of employees, total deposits received as inputs, while using total loans and short-term securities issued by official sector[16] as outputs. Berger and DeYoung add also transaction deposits (including NOW accounts) and fee-based income to the list of outputs. By Wheelock and Wilson (2000), *"banks are viewed as transforming various financial resources, as well as labor and physical capital, into loans, other investments and, sometimes, deposits. [Therefore,] … typically, various types of loans are categorized as outputs, while funding sources, labor and physical plant are treated as inputs"*. As can be seen, authors differ in the treatment of demand deposit. This can be explained by the fact that all the works differ in time they were written; and in the nearest past, interest was not paid for demand deposits, and therefore, they clearly could be considered as outputs. However, nowadays, demand deposits are typically remunerated, and therefore, demand deposits can be viewed as inputs. However, Wheelock and Wilson (1995) note that demand deposits require the large allocation of labor and capital, and therefore, they have to be important outputs[17]. Berger and DeYoung (1997) bolsters this viewpoint . Taking their suggestion into account, and since my aim is not to build new theory on measurement of efficiency, but to investigate, whether efficiency as it usually measured influences the probability of a bank to fail, my first output Y_1 is the *demand deposits*.

All of the authors advocate taking loans as outputs (*e.g.* Darrat, Topuz, and Yousef (2002), Wheelock and Wilson (2000)). However, some of them consider various types of loans as different outputs, while others use only total loans. By Tyampa (2001), banks-to-bank loans and bank-to-firm loans differ a lot: while

[16] Securities, as well as loans, are bank's investments, which earn profits. Thus, it is typical to consider them as outputs.

[17] Following Wheelock and Wilson (1995) I assume that interest paid for demand deposit is relatively small, and therefore, they can be treated as outputs.

the former earn small interest, and are highly safe, the latter are one of the most risky columns in banks' statistics, and earn a high interest. Therefore, I also distinguish between them, and consider *bank-to-bank loans* as output Y_2, and *bank-to-firm loans* as Y_3. Now the problem arises how to measure them.

There are two basic approaches to this issue. One approach, called the *production* approach, treats outputs as the number of loan and deposit accounts, while the *intermediation* approach measures outputs in dollar amount (Wheelock and Wilson (1995)). Because the statistics on the number of loans and deposits usually is not accessible, which is also the case for Ukraine, I decided in favor of the intermediation approach. Therefore, both deposits and loans are measured in hryvnya amount. The last output I use, Y_4, is investments, which reflect the value of *securities*.

In choosing inputs more consistency is observed. One of the typical inputs is the total of time and saving deposits. The choice is determined by the fact that "*interest was paid on such deposits and studies of modern banks indicate that substantially less labor and capital are devoted to maintain [these] … deposits than to maintaining demand deposits account*" (Wheelock and Wilson (1995)). Hence, one of the inputs, X_1, I use is total *time and saving deposits*, calculated as the sum of time and saving deposits of both firms and individuals.

The second input X_2 is also quite typical (Wheelock and Wilson (2000), Wheelock and Wilson (1995), Jemrić and Vujčić (2001), etc) – *capital* measured as a value of physical capital[18].

Unfortunately, our data set does not include any data on labor employed – either number of employees or spendings on them. Therefore, this classical input was

[18] Sometimes, researchers use fixed assets amount instead of physical capital amount, but data inspection reveal strong correlation among them.

not used in my research. However, correction for heterogeneity, which is presented below, implicitly takes it into account.

Thus, totally I used 2 inputs and 4 outputs for estimation: input vector consists of time and saving deposits and capital; output vector consists of demand deposits, interbank loans, loans to firms and households, and investments into securities.

Table 3 Definition of input and output sets used for the DEA analysis

Inputs	Outputs
Time and Saving Deposits	Demand Deposits
Capital	Interbank Loans
	Consumer and Business Loans
	Securities

With this set of outputs, it is also possible to get the *hryvnya* amount of inefficiency just by multiplying (1-E) by the sum of outputs: $Y_1+Y_2+Y_3+Y_4$, because all of them are measured in monetary units.

ii. Correcting for heterogeneity

Another big problem is that to measure efficiency and to get valuable results one has to be sure that the group of DMUs under consideration is homogeneous (Coeli *et al* (2002), Brown (2001), Schaffnit *et al* (1997)). In particular, I have to take into account differences in the environments banks are operating in. It seems obvious that banks in less "developed" oblasts (regions) are in less favorable conditions than those which are closer to big cities. The latter probably have richer clients, more opportunities for making safe loans, etc. This hypothesis will be the first I will check. To perform this test I will proceed in the following way. First, I will divide each dataset into 2 samples: banks which are in advanced region, and those which are not. Then, I will run DEA separately for both samples. Secondly, in both samples I will "push" all the banks up to the frontiers, providing correction for managerial inefficiency. All the remained difference between banks in the two subsamples will be due to environmental disparity. Therefore, my third step will be implementing of ANOVA technique, which will allow me to test whether this differences is significant, and will implicitly indicate its direction. I decided to calculate efficiency frontier separately for each year, because, as noted by Wheelock and Wilson (1995), the most efficient strategy in one year can be far from being the best in another year. To divide regions into the richer and the poorer I used region's revenue as an indicator, and called top 3 region – with highest revenue value – more developed, and hence – economically favorable. Based on UEPLAC[19] reports, these top regions are: Kyiv, Donetsk, Dnepropetrovsk. Typically, from 60% to 65% of all the banks in Ukraine belongs to these 3 out of total 24 regions. I got the following results for efficiency:

Table 4 Testing the hypothesis of no environmental differences

Date	Rich (Region=1)			Poor (Region=0)			Equal Means
	#Banks	*Mean*	*StDev*	*#Banks*	*Mean*	*StDev*	*p-value*
01.1999	71	40	29	59	35	29	0.40
07.1999	74	61	31	55	53	30	0.14
01.2000	76	62	28	55	53	28	0.07*
07.2000	69	70	22	56	56	26	0.00*
01.2001	78	71	23	49	65	22	0.15
07.2001	81	71	24	47	61	23	0.04*
01.2002	81	68	23	49	66	23	0.61
07.2002	79	40	28	47	41	31	0.80
01.2003	72	62	25	63	58	25	0.58

Note: p-values were obtained using ANOVA[20] techniques. H_0: means are equal; * - significant at 10%

[19] UEPLAC=Ukrainian-European Policy and Legal Advice Centre

[20] Strictly speaking, ANOVA leads to biased results because the dependent variable we use is specific – it is limited from both the bottom and the top. However, there are at least two reasons, which advocate in

As can be seen from the table, all the years except one mean efficiency of those banks belongs to rich regions exceeds that of poor regions, however, this difference was significant only in 3 out of 8 cases. Therefore, for these 3 time-points correction for heterogeneity was done; for other time-points usual (non-corrected) efficiency was calculated.

As Darrat, Topuz and Yousef (2002) note, the product of the number of inputs to the number of outputs has to be less than or equal to sample size, which is clearly the case in my research: every year under consideration more than 100 banks were observed. Summary statistics of my findings is presented in *Table 3*.

Table 5 Comparative efficiency measurement results for failed and sound banks from Jan 1999 to Jan 2003

	Median Efficiency, %	Mean Efficiency, %			Mean Corrected Efficiency, %		
	All banks	*All banks*	*Failed*	*Sound*	*All Banks*	*Failed*	*Sound*
01.1999	26	37	27	38	49	31	50
07.1999	53	58	61	57	68	73	67
01.2000	51	59	62	57	68	71	69
07.2000	63	63	64	63	74	74	75
01.2001	67	68	53	69	77	56	78
07.2001	60	67	84	66	78	85	77
01.2002	62	67	68	67	78	82	76
07.2002	29	40	40	41	49	60	49
01.2003	56	61	-	-	61	-	-
Total		57			68		

Note: To calculate total efficiency I weighted mean year efficiency with the number of banks this year. Here, corrected efficiency is calculated for all the periods under consideration.

favor of ANOVA: first, it seems to be one of the most appropriate methods, because it allows not just to compare means, neglecting standard deviations (as in Sathye (undated), Jemrić and Vujčić (2001)), but also to test and get a meaningful p-value (Canhoto, Dermine (2000)); and secondly, small bias seems to be acceptable, because measurement of efficiency is not the primarily aim of this research.

We can see that efficiency of sound banks *does not* exceed that of failed ones. Moreover, in the majority of cases both corrected and usual efficiencies of failed banks were higher than that of sound. This, however, cannot be an indicator that *ceteris paribus* this would also be the case: to test this conclusion we need to apply regression analysis, which will be presented in the next section.

The mean efficiency score for the Ukrainian banks is 57% in the first model and 68% in the second one. Besides the fact that it lies within the range found in other studies, it is much smaller than the world's average 86% (Berger and Humphey (1997)), and 57% value of the uncorrected Ukrainian banks' efficiency approaches closely the world's minimum efficiency score of 55% for UK banks in Berger and Humphey (1997) cross-country estimation. All this imply that Ukrainian banks need to improve their performance, and the government also should help them by developing and implementing an appropriate policy. These conclusions cannot be considered as strict ones, because efficiencies are calculated with respect of the best bank, which could differ a lot between countries; however, there is a rationality behind them, taking into account that there are currently 6 foreign banks in Ukraine, which make the results more-or-less comparable.

Comparison of mean and median efficiencies indicates the presence of relatively small number of outliers with low productivity and efficiency. Hence, efficiency is skewed to the left. These results are similar to Wheelock and Wilson (1995) findings on a Kansas sample of banks where efficiency was also skewed toward zero each year.

To conclude this part of the work, I found the efficiency score for each of the bank each period of time under consideration. For several periods (01.2000, 07.2000, and 07.2001) I have to adjust the score for environmental differences, which occurred to be significant. As *Table 5* shows, we cannot make any predictions on bank's state (either failed or sound) based solely on efficiency score – efficiency of sound banks does not exceed that of insolvent. Thus, to proceed further we need econometric analysis.

Chapter 5

ECONOMETRIC MODEL

Theory overview

In this section I will perform both multiperiod logit (known also as *Giant Logit*) and parametric survival estimation. To begin with, I need to choose the variables I will use in both regression models, which probably influence the probability of a bank to become unsound.

First, as can be seen from the data description (*Table 1*), total assets in the banking sector (as well as capital, funds, etc.) grew up by a significant percentage during the period of study (from 14 billions hrn in 1999 to 59 billions hrn in 2002), while the total number of the banks remained virtually unchanged. Therefore, the usage of level variables seems to be problematic due to danger of heteroscedasticity. Thus, I decided in favor of the usage of ratios. Secondly, in the process of researching I will follow the standard C.A.M.E.L. scheme[21] (Capitalization, Assets, Management, Earnings, Liquidity), which seems to be the most typical in case of banks' situation analysis.

(C)apital. – Total Capital, the bank's net worth, is an important source of bank's funds. The main role of the capital is *"a cushion against drop in the value of its assets, which could force the bank into insolvency"* (Mishkin, Eakin (1999)). It allows total assets to decline as a result of, e.g., writing off worthless loans, and still remain bigger than liabilities. Many economists claim that capital crunch was one of the main reasons of US banks failure on mid 1980s. Therefore, it seems to be required to

[21] CAMEL is a typical scheme US Federal regulators base there evaluation on

be taken into account while doing econometric analysis. The most typical way to do this is to form capital/assets ratio. Altman (1968), Hajdu and Vigar (undated), Shumway (2001) and others include capital/assets ratio, Dabos and Escudero (2000) proceeded in similar way, including liabilities/capital proportion, Wheelock and Wilson (1995) even treat the bank as bankrupt if its capital/assets ratio is smaller that 2%. Hence, the first two variables I use are *CAPITAL/NET_ASSETS* (where CAPITAL refers to Total Capital) and authorized capital to assets (*AUTH_CAPITAL/NET_ASSETS*) ratio; with expected negative influence on the probability of failure. These variables also implicitly serve to account for liquidity (Altman (1968)).

(A)ssets. - High value of CIP (Credit-Investment Portfolio) in the bank's assets can be a consequence of considerable problems: for example, in the case when most of the loans are bad loans, and all other assets were already spent. Therefore, *CIP/NET_ASSETS* it is an indicator of assets quality. However, CIPs also differ in quality. To reflect this difference I included its compounds as different variables. The first component is Industrial loans, *IND_LOANS/CIP*, which are *"typically the less liquid and most risky of bank assets"* (Wheelock and Wilson (2000)), and therefore, I expect that the bigger is the share of loans in the total amount of assets – the higher will be the probability of the bank to become insolvent; therefore, expected sign is positive. The second component is investment into securities. In the most of other research this variable ex ante was expected to influence negatively failure probability; however, in our case its influence is ambiguous, because a certain part of the investment into securities should be the investment into Ukrainian companies (one of the requirements of the NBU), and thus, taking into account the volatility of Ukrainian market, is quite risky. Therefore, the influence of this variable is ambiguous. The last part of CIP is interbank loans. It is just a linear combination of the first two components, and therefore, should not be included into the regression.

(M)anagement. - To measure the impact of managerial efficiency I include *EFFC* variable, which measures corrected (for heterogeneity) efficiency of Ukrainian banks. For some specifications I also use *EFF* – uncorrected (usual) DEA efficiency, and *SEFF* – super-efficiency, which also were described above.

(E)arnings. - To gauge the performance of a bank and to measure its earnings I used returns to capital (ROE) equals the ratio of bank's profits to capital (*PROFITS/CAPITAL*). This measure is also quite typical and was used by Wheelock and Wilson (2000), Wheelock and Wilson (1995), Dabos and Escudero (2000), Shumway (2001), and others.

(L)iquidity. - To measure liquidity or at least to take it into account I use the ratio of deposits to bank's assets. The main argument is that banks, which have significant values of deposits (comparing with its 'size' – value of assets) may experience significant problems when, say, economic situation worsen, and depositors decide to withdraw their deposits. Because terms and conditions may differ for individual and business depositors, I included both the ratio of individual deposits to assets (INDIV_DEPS/NET_ASSETS) and the ratio of business deposits to assets (BUSIN_DEPS/NET_ASSETS). It is obvious that time and saving deposits and demand deposits differ a lot; therefore, another two variables are the share of demand deposits in individual deposits (DEMAND/INDIV_DEPS) and that in business deposits (DEMAND/BUSIN_DEPS).

Besides C.A.M.E.L. variables, I also need to include into analysis several other factors. The first one is the logarithm of assets (*LOG(ASSETS)*), which reflects the size of a bank assets. I also introduce in the model the set of dummy variables *DATEmmyy*, equals "1" for the month *mm* in year *yy*, and "0" - otherwise. Their purpose is to capture the differences in economic situations each period, and these variables will be used in logit estimation. Next variable I use is

REGION, which, as in the case of DEA analysis, equals 1 for the three most developed regions: Kyiv, Donetsk, Dnepropetrovsk, and its purpose is to take into account environmental differences. And the last is the dependent variable – *FAIL*, which is a dichotomy variable that equals 1 for a bank which does not appear in the next period statistics, i.e. failed, and 0 – otherwise. Unfortunately, my data set does not distinguish between failure and, say, acquisition, or exit for other reasons, but these problems are also quite typical (*e.g.* Shumway (2001)).

Table 6 Statistics on Variables Used

#	*Variable*	*Expected*	*Median*	*St.Dev.*
1.	FAIL	-	-	-
2.	AUTH_CAPITAL/NET_ASSETS	-	0.057	0.153
3.	CAPITAL/NET_ASSETS	-	0.332	0.207
4.	CIP/NET_ASSETS	+-	0.648	2.346
5.	INDIV_DEPS/NET_ASSETS	+	0.109	0.132
6.	BUSIN_DEPS/NET_ASSETS	+	0.247	0.177
7.	DEMAND/INDIV_DEPS	+	0.125	0.239
8.	DEMAND/BUSIN_DEPS	+	0.722	0.220
9.	EFFC (corrected efficiency)	-	69.31	29.13
10.	EFF (simple efficiency)	-	53.24	29.32
11.	INDUST_LOANS/CIP	+	0.746	0.193
12.	LOG(ASSETS)	-	4.310	1.341
13.	NET_ASSETS/NET_LIABS	-	1.146	127.6
14.	PROFITS/CAPITAL	+-	0.031	0.089
15.	REGION	-	-	-
16.	SECURITIES/CIP	+-	0.057	0.142
17.	DATEmmyy	+-	-	-

Multiperiod Logit

i. Theoretical background

Equation 9 represents what is known as the cumulative logistic distribution function[22]. It can be seen that while $X\beta$ varies from -∞ to +∞, p_i ranges from 0 up to 1:

$$p_i(y_i = 1) = E(y_i = 1 \mid \vec{X}_i \vec{\beta}) = \\ = 1 - \frac{\exp(-\vec{X}_i \vec{\beta})}{1 + \exp(-\vec{X}_i \vec{\beta})} = \frac{\exp(\vec{X}_i \vec{\beta})}{1 + \exp(\vec{X}_i \vec{\beta})} \tag{9}$$

To provide a possibility to estimate non-linearity in the dependant variable, it is possible to construct so-called *odds ratio* – the ratio of p_i to $(1 - p_i)$. If then we take the natural logarithm of this ratio, we will get a simple specification, linear not only in X but also in parameters:

$$\Lambda_i = \ln\left(\frac{p_i}{1 - p_i}\right) = \vec{X}_i \vec{\beta} \tag{10}$$

Λ is called the *logit*. However, Λ only, not the probability p, is linear in X, and therefore, to get an expression for the *marginal effect* – change in p with respect to one unit increase in X_k – one needs to take a derivative of p with respect to X_k:

$$\frac{\partial p(\vec{X}_i \vec{\beta})}{\partial X_k} = \frac{\exp(\vec{X}_i \vec{\beta})}{\left[1 + \exp(\vec{X}_i \vec{\beta})\right]^2} \beta_k \tag{11}$$

In my thesis I will run not logit, but giant logit. However, the only difference between the usual logit and the giant logit is that while talking about giant logit, one usually means that the purpose is to run logit on pooled paned data, allowing

22 Theory overview was taken from Gujarati (1995)

for different constant terms in each year; in practice – just by adding dummies for all the periods except one.

ii. Estimation using logit model

For the initial specification I included all the variables listed in the *Table 6*. After exclusion of insignificant variables, I got several final specifications – *Table 7*. The *Model 1* reports estimates when all the variables are included. However, we can rely neither on p-values nor on coefficients estimates (and hence - signs) we got because Logit produces biased, inconsistent and inefficient estimates when any misspecification takes place (Johnston, DiNardo (1997)). Full model was simplified by exclusion of (jointly) insignificant variables based on Likelihood Ratio (LR) test[23]. Several alternative final specification can also be seen in *Table 7*.

For all the specifications I got meaningful signs: Efficiency influences bank failure negatively, i.e. the more efficient the bank is – the smaller is the probability that it will become unsound. The impact of *EFFC* and *EFF* do not differ a lot, neither in the magnitude, nor in the level of significance. Big share of Securities in CIP seems to be a good indicator of possible problems, and high ROE (returns to equity, which equals *PROFITS/CAPITAL*) pushes the probability of bankruptcy downward. As was expected, banks in "rural" (less developed) regions are more risky. Size also does matter, which is clear from the significance of *LOG(ASSETS)* variable in the *Model 4*. Besides the fact that *EFFC* variable is significant, its influence is equivocal, which is clear while comparing *Model 3* and *Model 4*: in another sequence of top-bottom exclusion, *EFFC* variable becomes insignificant (together with *REGION* and *DEMAND/INDIV_DEPS*) in favor of *LOG(ASSETS)*.

[23] LR test: $-2\ln(RLF/ULF)\sim\chi^2$, with df=the number of restrictions. RLF and ULF are respectively restricted and unrestricted likelihood functions. H_0: restrictions are valid.

Table 7 Logit estimation

Dependent variable: FAIL				
Variable	Coefficients			
	Model 1	*Model 2*	*Model 3*	*Model 4*
C	2.66	-0.75***	-2.27***	-0.28
	(0.19)	(0.00)	(0.00)	(0.14)
EFFC	0.00	-0.01**	–	-0.00
	(0.36)	(0.03)		(0.75)
EFF	–	–	-0.01**	–
			(0.04)	
SECURITIES/CIP	0.56	1.01***	2.27***	0.70**
	(0.68)	(0.00)	(0.00)	(0.03)
PROFITS/CAPITAL	-18.82**	-2.72***	-9.92***	-1.97***
	(0.05)	(0.00)	(0.00)	(0.01)
REGION	0.09*	-0.19*	-0.26	–
	(0.77)	(0.07)	(0.39)	
DEMAND/INDIV_DEPS	0.47	0.38*	1.14*	–
	(0.46)	(0.07)	(0.06)	
LOG(ASSETS)	-1.02***	–	–	-0.15***
	(0.00)			(0.00)
CAPITAL/NET_ASSETS	-0.25	–	–	–
	(0.83)			
CIP/NET_ASSETS	-0.65	–	–	–
	(0.24)			
DEMAND/BUSIN_DEPS	-0.60	–	–	–
	(0.43)			
BUSIN_DEPS/NET_ASSETS	1.08	–	–	–
	(0.21)			
INDUST_LOANS/CIP	-0.29	–	–	–
	(0.77)			
DATE0199	-0.88	–	–	–
	(0.26)			
DATE0799	-1.41*	–	–	–
	(0.06)			
DATE0100	-0.93	–	–	–
	(0.19)			
DATE0700	-1.23	–	–	–
	(0.23)			
DATE0101	-1.27*	–	–	–
	(0.10)			
DATE0701	-1.87	–	–	–
	(0.11)			
DATE0102	-0.13	–	–	–
	(0.84)			

Note: p-values in parenthesis. * indicates that variable is significant at 10%, ** - 5%, *** - at 1%.

To move from pure econometric significance to economic one, we have to know not only whether a variable is significant, but also how strong its influence is. To do this we need to find marginal effects. Because the means of variables differ a lot (some variables are less than 0.01, others – about 100), marginal effects only will not bear a lot of information; therefore, it seems meaningful to find an effect of a change in dependent variable by one standard deviation on the probability to fail. These 'modified marginal effects' are presented at the *Table 8*.

Table 8 Calculation of the modified marginal effects for a median bank, giant logit model

Variable	Effect of one St.Dev. increase, %		
	Model 2	*Model 3*	*Model 4*
EFFC	-4.1	–	0.0
EFF	–	-1.2	–
SECURITIES/CIP	2.0	1.3	1.9
PROFITS/CAPITAL	-3.4	-3.5	-3.4
REGION	-2.7	-1.0	–
DEMAND/INDIV_DEPS	1.2	1.0	–
LOG(ASSETS)	–	–	-3.8

Note: Effect of one St.Dev. change was calculated as a product of usual one unit change marginal effect times the share of one standard deviation change in one unit change; mathematically – just by multiplying marginal effect by the standard deviation. Therefore, calculated effect is only a proxy for the real value. I choose a median bank as a baseline.

Thus, increase in efficiency by one standard deviation decreases the probability of a bank to fail by 4.1%, suggesting that managerial efficiency plays a significant role in determinants of bank's failure. However, specification 4 contains insignificant *EFFC* variable, but highly significant *LOG(ASSETS)*, indicating that the influence of *EFFC* should be treated with the grain of salt. Effects of one standard deviation increase of *SECURITIES/CIP* and *PROFITS/CAPITAL* variables are almost the same in all specifications, and equal about 1.8% and 3.4% correspondingly. Marginal effect of *REGION* variable shows that choosing a bank in a developed region will decrease the probability to loose money by 0-2.7% on average.

However, calculation of marginal effects is not everything we need: another important issue is how well our model performs. The standard way of evaluating the model is to look at how well it predicts. Usually, it is done by calculating the percentage of correct predictions of '1's, and that one of '0's. Of course, the model 'returns' not the dichotomy variable 0-1, but an unobserved index. It is common practice to treat the values of this index which exceed 0.5 can be treated as 1's, and those, which are less than 0.5 – as 0's. However, this is not always correct, and even more – this threshold works well only when the number of 0's and 1's is roughly the same in the dependent dichotomy variable. When it is not the case – it is better to take the threshold which is the number approximately equal to the share of 1's in all observations. The exact value of this threshold can be chosen based on the following considerations. Every researcher has to choose a loss function. The need in the loss functions appears because in this kind of problems we always have a trade-off: we can increase the percentage of correct predictions of 1's, i.e. of correct predictions (limiting case: threshold equals 0 and get 100% of correct predictions), but this will decrease[24] correctly predicted 0's (this percentage will reach maximum of 100% when the threshold equals 1). One of the typical loss functions (strictly speaking: gain function) is to look at the *total percentage gain* of the model comparing to the constant probability model. But this is not the only possible choice: if, for example, a researcher values correct predictions of bankruptcy two times more than that of soundness (which is quite natural: its better to overestimate the risk than underestimate it), than she can maximize $G=2(\%1)+(\%0)$ by choosing an appropriate value of threshold. Because the main goal of my work is to find out what are the determinants of

[24] When the dataset is not very large or it is homogeneous it can happen that when one changes the threshold, only one of the predictions probabilities changes; but it's the case only because of discretion

possible bank's problem (which are independent on the level of the threshold as well as estimated probabilities to fail), I choose the most common Total Percentage gain as my loss function, and varied the threshold to maximize it. The results are shown in *Table 9*.

Table 9 Goodness of fit of logit models

	Model 1		*Model 2*		*Model 3*		*Model 4*	
Values:	1	0	1	0	1	0	1	0
Correct predictions, %	80	61	72	56	74	56	80	66
Total gain, %	71		69		70		73	
LR statistics, p-value	0.00		0.00		0.00		0.00	
Hosmer-Lemeshow, p-value	0.34		0.66		1.00		0.24	

Note: I took the threshold value that equals 0.04. The description of Hosmer-Lemeshow test can be found in Eviews 4 User's Guide. H_0 is "the model is good"

Based on *Total gain*, the model that performs the best seems to be the *Model 4* – it correctly reveals 80% of the bank, which will fail next period, and 66% – of that which will stay sound. These results are comparable with those obtained in other studies: for example, in Zmijevski (1984), Total gain (TG) equals 71% and the estimation was done by Probit model; TG in Harland *et al* (1990) equals 95%. However, taking into account that Ukraine is a transition country with unstable and young banking system, and the fact that there are many factors other than economical (say, political) which leads to bankruptcy of some banks, the performance of the obtained model seems to be quite good. Another factor which advocate in favor of my model is that in most of other research the official data were available, while in case of Ukraine everything we have are partially unofficial data from Ukrainian Banks Association with a limited number of indicators published.

Based on *Model 4*, I made prediction for the next period, which you can see in the *Table 10*. In the column named *White List* are those banks, which have the smallest probability to fail next period, while those, with the greatest probability to become unsound fall into *Black List* column.

Table 10 List of the banks with the smallest and the highest probability to fail until July, 2003 predicted by Logit model

"White" List		"Black" List	
Name	*P of Fail*	*Name*	*P of Fail*
Privatbank	0.00196	Yevropeyskiy	0.11010
Express-bank	0.00313	Avtokrazbank	0.11606
Financy i Credit	0.00600	Bank Klassic	0.11682
Aval	0.00610	Fermerskiy Zamelnyy	0.13928
Ukrsotsbank	0.00751	Avtoritet	0.14817
Derzhavnyy Exp-Imp Bank	0.00790	Prime Bank	0.15346
Citibank Ukraina	0.00827	Invest Krivbas Bank	0.15819
Ukrsibbank	0.00904	FEB	0.16185
PUMB	0.00990	Slavutich	0.17395

Note: banks were sorted by the probability of failure, and then top 9 and bottom 9 were put in the table.

It is probably worth to mention that my findings are close to that of Standard&Poor's – international ranking agency – which referred to Privatbank, Aval, Ukrsotsbank, and PUMB as the most reliable banks in Ukraine. They were the only Ukrainian banks which entered its Top-100 Central-Eastern Europe banks' ranking[25].

The next stage is running duration model, and comparing its performance with that of the logit model.

[25] UABanker Information Agency, http://www.uabanker.net/daily/2002/10/102402_1520.shtml

Duration Analysis

The second model I used is duration analysis, mainly the parametric accelerated failure-time (AFT) model, which models the natural logarithm of the survival time is expressed as a linear function of the covariates:

$$\ln(t) = \vec{x}\vec{\beta} + \varepsilon \tag{12}$$

the distributional form of the error term determines the regression model.

i. Theoretical background[26]

Basically, survival models investigate time to failure over a given observation period. Let *T* represents the lifetimes of unit, and let *f(t)* be the probability density function of *T*. Then, the distribution function takes the form:

$$F(t) = \int_0^t f(t)dt = \Pr(T \le t) \tag{13}$$

The probability that an individual managed to survive till time *t* is given by the survival function:

$$S(t,x) = \int_t^\infty f(x)dx = \Pr(T \ge t) \tag{14}$$

And another useful concept typically used in duration analysis is the hazard function *h(t, x)*, which specified the rate of failure at time *t* given that a unit had survived till time *t*:

$$h(t,x) = \frac{f(t,x)}{S(t,x)} \tag{15}$$

[26] Based on STATA 7.0 User's Manual, Lawless(1982) and Greene(2000)

Certainly, all the functions *f(t)*, *F(t)*, *S(t)*, and *h(t)* give mathematically equivalent specifications of the distribution of *T*. Therefore, either of them can be used.

To proceed with calculations, I need firstly to specify a particular distribution of the hazard function. One of the natural choices in this situation is log-logistic distribution[27]:

$$h(t,\lambda) = \frac{\lambda^{\frac{1}{\gamma}} t^{\frac{1}{\gamma}-1}}{\gamma\left\{1+(\lambda t)^{\frac{1}{\gamma}}\right\}} \tag{16}$$

which leads to the following *S(t)* and *f(t)*:

$$f(t,\lambda) = \frac{\lambda^{\frac{1}{\gamma}} t^{\frac{1}{\gamma}-1}}{\gamma\left\{1+(\lambda t)^{\frac{1}{\gamma}}\right\}^2} \tag{17}$$

$$S(t,\lambda) = \frac{1}{1+(\lambda t)^{\frac{1}{\gamma}}} \tag{18}$$

Next, *"this model is implemented by parameterizing* $\lambda_j = e^{-x_j\beta}$ *and treating the scale parameter* γ *as a ancillary parameter to be estimated"* (Stata's Manual). As can be seen from the hazard function, for $0<\gamma<1$ the probability of failure of a bank rises with time, but then when *t* reaches some critical value, this probability starts to decline. It can be explained by the following. When bank is established, it has some minimum requirements of capital, which it uses as a buffer in case of problems: decline in assets, etc. If things go wrong – either because of bad management, or extreme competition – this capital steadily declines, and at the

[27] Other possible choices include Weibull distribution, which leads to monotonic hazard, and exponential distribution, which results in constant hazard. Both of them will also be considered.

end the bank becomes bankrupt. But if it managed to survive and cope with its problems, then learning-by-doing starts to play a significant role, and, ceteris paribus, it decreases in time the probability to fail. Therefore, it is natural to expect that this log-logistic hazard is quite realistic. The second argument to bolster this decision is that studies with non-time-varying covariates and non-parametric hazard find found that it clearly has a maximum (Borovikova (2001), Dabos and Escudero (2000), etc).

With γ exceeds 1, we have just a permanent decline of the hazard with time. Another problem I faced is that interpretation of β*'s* is not straightforward, neither in direction nor in magnitude. Unfortunately, at my knowledge, neither work on this issue (at least in banking sector analysis) calculates marginal effects, and thus – lack of comments on *economic* significance of various variables, and therefore, on possible policy implications. I tried to correct this drawback and present the results, which I hope will be useful for future researchers. To calculate the marginal effect (on hazard) I need just to take a derivative of hazard with respect to x_i:

$$\frac{\partial h(t,\lambda)}{\partial x_i} = \frac{\partial h(t,\lambda)}{\partial \lambda} \cdot \frac{\partial \lambda}{\partial x_i} = -\beta_i \lambda \frac{\partial h(t,\lambda)}{\partial \lambda} \tag{19}$$

while

$$\frac{\partial h(t,\lambda)}{\partial \lambda} = \frac{t^{\frac{1-\gamma}{\gamma}}}{\gamma^2 \lambda^{\frac{1+\gamma}{\gamma}}} \cdot \frac{1}{\left\{\lambda^{-\frac{1}{\gamma}} + t^{\frac{1}{\gamma}}\right\}^2} \tag{20}$$

The expression in the *Equation 20* is strictly positive for non-zero value of time, which makes *Equation 19* negatively related to β. Thus, maybe somewhat counterintuitively, positive β_i implies that X_i decreases the probability of a bank to fail, while the negative sign implies the opposite.

ii. Estimation using log-logistic Hazard model

The estimation was done by STATA 7.0, namely by *stset* and *streg* procedures. All the outputs by default present the estimates of the hazard metric. *DATEmmyy* dummies are not used here, rather, it was substituted by a discrete variable *TIME* with values equal the number of period; however, the model needs additional variable to be constructed – *ENTER*, which equals 1 if a bank enters the universe this period, and 0 – otherwise. The purpose of this variable is to allow for left truncation. Right truncation was allowed implicitly by specifying *FAIL* variable – those banks, which did not failed till the last period of observation, are treated as truncated from the right. Obtained outputs can be seen in the *Table 11*. The first model includes all the variables, while *Model 2* – only those, which were not excluded as jointly insignificant by LR test. The purpose of *Model 3* is to evaluate which of the two variables – *EFF* of *EFFC* – captures the bank's state better. *Model 4* includes constant term only, and can be treated as a regression for a mean bank. *Model 5* is a model with the underlying assumption of constant (rather than log-logistic) hazard. Its purpose is to show (test) the superiority of log-logistic assumption over constant probability of failure assumption.

The main model to be discussed is *Model 2*. It can be seen that those banks, which have higher share of demand deposits in the total value of individual deposits, have, ceteris paribus, higher probability to fail. The same is true for higher share of securities in credit-investment portfolio (CIP). Efficient banks have smaller probability to become unsound, which is reflected in the significance of *EFFC* variable. Comparing *Model 2* and *Model 3*, we see that it seems that corrected efficiency (*EFFC*) is a better predictor of bank's state than simple efficiency (*EFF*), which is insignificant at 10% level. And the last but not the least variable, which an investor has to pay attention to, is *LOG(ASSETS)*. The higher is the value of this variable – the smaller is the probability that a bank will go bankrupt. It looks like that other variables do not really influence significantly the probability to fail.

Table 11 AFT Output Produced by
STATA 7.0

	Log-Logistic				*Exp*	*Weibull*
	Model 1	*Model 2*	*Model 3*	*Model 4*	*Model 5*	*Model 6*
C	-0.07	0.22	0.36	2.54***	–	-0.34
	(0.74)	(0.66)	(0.29)	(0.00)		(0.66)
DEMAND/INDIV_DEPS	-0.33	-0.47	-0.42	–	1.76	-0.44
	(0.28)	(0.13)	(0.20)		(0.37)	(0.15)
LOG(ASSETS)	0.43***	0.46***	0.48***	–	0.54***	0.51***
	(0.00)	(0.00)	(0.00)		(0.01)	(0.00)
SECURITIES/CIP	-0.82	-1.33***	-1.24**	–	3.19	-0.68
	(0.16)	(0.01)	(0.02)		(0.35)	(0.23)
EFFC	0.01**	0.01***	–	–	0.99	0.01*
	(0.05)	(0.01)			(0.35)	(0.09)
EFF	–	–	0.01	–	–	–
			(0.11)			
BUSIN_DEPS/NET_ASSETS	-0.35	–	–	–	3.62*	-0.63*
	(0.33)				(0.09)	(0.10)
INDIV_DEPS/NET_ASSETS	0.37	–	–	–	0.49	0.59
	(0.54)				(0.63)	(0.44)
DEMAND/BUSIN_DEPS	-0.03	–	–	–	0.83	0.01
	(0.94)				(0.80)	(0.98)
INDUST_LOANS/CIP	0.13	–	–	–	0.76	0.24
	(0.77)				(0.76)	(0.57)
CIP/NET_ASSETS	0.17	–	–	–	0.81	0.16
	(0.34)				(0.55)	(0.39)
CAPITAL/NET_ASSETS	0.67	–	–	–	1.63	0.86
	(0.16)				(0.66)	(0.13)
PROFITS/NET_ASSETS	1.00	–	–	–	0.01	0.41
	(0.45)				(0.14)	(0.77)
REGION	0.03	–	–	–	0.90	0.06
	(0.86)				(0.75)	(0.71)
NET_ASSETS/NET_LIABS	-0.00*	–	–	–	0.99	0.00
	(0.08)				(0.74)	(0.84)
AUTH_CAPITAL/NET_ASSETS	-0.74	–	–	–	0.46	-0.72
	(0.13)				(0.46)	(0.14)
Gamma	0.43***	0.47***	0.49***	0.76***	–	2.14***
LR χ^2	53.41	48.43	45.15	–	33.94	50.06

Note: p-values in parenthesis. *Models 1-4* use non-monotonic (log-logistic hazard), while *Model 5* and *Model 6* – constant (exponential) and monotonic (Weibull) hazards respectively (interpretation of the coefficients differs). * indicates significance at 10%, ** - at 5%, *** - at 1%.

In all the cases absolute value of *Gamma* is less than 1, which indicated that hazard has a peak. So, its interesting to look at a hazard of a average new bank, and investigate where hazard has a peak (i.e. what is the 'critical time', at which probability to fail reaches maximum), and starts to fall. Also it is interesting to compare this hazard with that of a big (and typically – old) and that of a medium (usually - middle-aged) bank. Banks are ranked as 'big' and 'medium' (as well as 'small') by the value of its assets, as it is done in NBU Herald reports: big banks are those which have assets more than 1 billion UAH, middle – those which assets are more than 100 millions UAH.

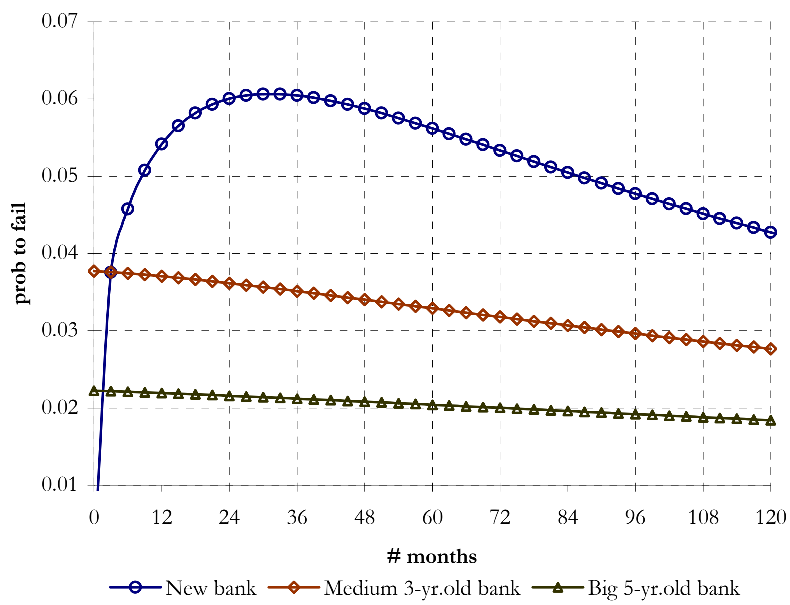

Figure 3 Hazard function for a mean newly-established bank comparing to the probability to fail of a 5-year old large and 3-year old medium banks

As we expected, hazard has a peak, and the critical time is about 30[28] months. Starting from that time probability to fail starts to go down, indicating probably that learning-by-doing starts to play a significant role. Average medium bank, which has been operating more than 3 years, has much smaller probability to fail than newly-established one, and an average old 5-year old bank in its turn is superior to a medium one in terms of its reliability. Certainly, these results do not show that only big banks are worth doing business with, at least because of cost-benefits analysis: for example, small (and new) banks can offer much more favorable conditions to their business partners and depositors. And of course, these results are quite rough, taking into account that the hazard can be built only for a bank for which we assume all the variables to be constant over time. However, it can serve as a pattern of what is going on in real life.

Another important issue is the estimation of marginal effects. Calculation of marginal effects is not straightforward because of at least two reasons. First, as it was in case of logit, they results of calculations depend on the point we are calculating at, i.e. they depend on particular values of independent variable(s). And another problem, which did not appear before, is that in case of duration analysis the results of marginal effects estimation also depend on time. Therefore, we have to fix both exogenous variables and time to be able to calculate marginal effects. Thus, I took an average bank, and calculated marginal effects at different points in time: in 6 months, 1 year, 3 years, and 10 years. Because of the reasons described in case of Logit estimation, I give the values of not pure but rather modified marginal effects, which were previously multiplied by the standard

[28] However, I need to emphasize that despite high econometric significance of the variables in the regression, confidence interval for critical time is quite wide. 90% confidence interval ranges from about 10 to 51 months.

deviation[29] of the independent variable we are calculating marginal effect of. The model I am analyzing is *Model 2*. Marginal effects are listed in *Table 12*.

Table 12 Modified Marginal Effects for a mean bank, %; AFT model

Variable	Effect of one St.Dev. increase, %			
	6 months	*1 year*	*3 years*	*10 years*
DEMAND/INDIV_DEPS	0.8	1.6	2.1	0.2
LOG(ASSETS)	-4.3	-9.0	-11.8	-1.1
SECURITIES/CIP	1.3	2.7	3.6	0.3
EFFC	-0.8	-1.7	-2.2	-0.2

As can be seen from *Table 12*, all the variables have similar in magnitude marginal effects, especially taking into account that increase of *log(Assets)* by one standard deviation is relatively harder task, than changing ratios, especially taking into account significant skewness of Assets distribution. The impact (absolute value) of marginal effects also has its maximum, and then steadily diminishes in time. In all the cases, this maximum will lie to the left from the peak of hazard. This can easily be verified using simple math. Using formulas (19) and (20) it can be shown that marginal effect (ME) equals:

$$ME = -\beta \frac{h(t,\lambda)^2 t}{(\lambda t)^{\frac{1}{\gamma}}} \tag{21}$$

and taking into account that $\gamma<1$ it is obvious that the extremal time of ME is less than that of hazard ($t^*_{ME} < t^*_{hazard}$). *Figure 4* supports these findings. Therefore,

[29] For simplicity, I used the standard deviation of polled variable

that shows that probably the policy of bank's management can be quite effective – its impact rises when things go worst, and the speed of rising is so that it surpass the worsening of bank's state of affairs. However, the same is true about mismanagement – when the probability of a bank to bankrupt is on its ridge – mismanagement is especially destructive.

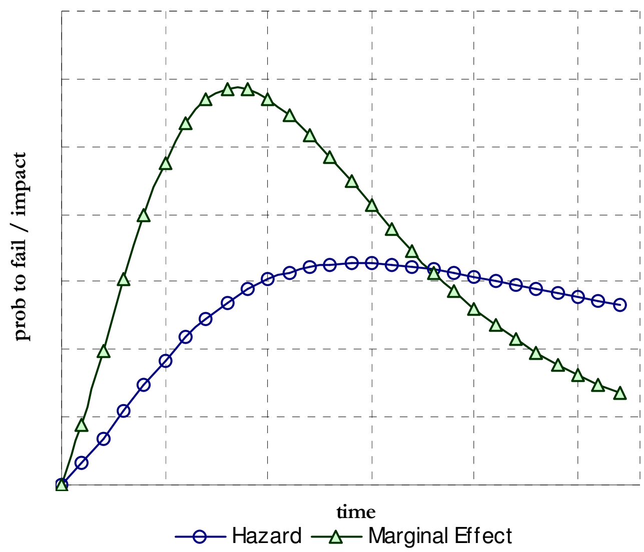

Figure 4 Comparison of patterns of
Marginal Effects and Hazard

As in the case of Logit, I did goodness-of-fit test. To make possible the comparison of hazard model results and those of logit, I used similar methodology, namely I estimated predicted time to fail[30] for all the banks in every period of time, and then build the expectation-prediction table. Varying the cut-offs (here: some critical time) as in the case of logit estimation, I maximized Total gain. The results are presented in the *Table 13*.

[30] Another possibility – to predict hazard

Table 13 Goodness-of-fit for the AFT model

	Model 1		*Model 2*		*Model 3*		*Model 5*		*Model 6*	
Values:	1	0	1	0	1	0	1	0	1	0
Correct predictions, %	81	48	77	52	64	62	69	53	55	66
Total gain, %	65		65		63		61		61	
LR statistics, p-value	0		0		0		0		0	

As can be seen from the *Table 13*, there is almost no difference between full model (*Model 1*), and the simplified one (*Model 2*), which again supports the conclusion that all the variable which did not enter the specification of *Model 2* do not really play a significant role in bank's bankruptcy. *EFF* performs worse than *EFFC*, which is reflected by the relative performance of *Model 2* and *Model 3*. In spite of the fact that constant hazard model (*Model 5*) slightly yields to log-logistic model, the difference is not big – 4%. So does monotonic (Weibull) hazard model – *Model 6*.

Similar to logit modeling, to make my research more useful, I would like to present you the forecast (or ranking) of the banks by their probability to fail till the end of the next period – July, 2003, made by using duration (AFT) analysis. The banks were sorted by their hazard, and top 10 (with the least hazard) were put into the "White" list, and bottom 10 – fall into the "Black" list. Both lists are presented in *Table 14* below.

Table 14 List of the banks with the smallest and the highest probability to fail until July, 2003 predicted by AFT model

"White" List		"Black" List	
Name	*Hazard*	*Name*	*Hazard*
Privatbank	0.035	Real bank	0.120
Aval	0.043	Invest Krivbass bank	0.121
Pivdennyy	0.046	Olbank	0.124
Ukrsibbank	0.047	ChBRR	0.126
Khreschatik	0.050	Fermerskyy Zemelnyy	0.128
Nadra	0.051	Yevropeyskyy	0.128
Praveks	0.055	Pivdenkombank	0.129
Forum	0.056	Factorial bank	0.136
Finansy i Credit	0.057	Bank Klassik	0.147
Raiffaizenbank Ukraina	0.058	Pekao Ukraina	0.170

One can see that in spite of the fact that the members of both White and Black lists are roughly the same by Logit and AFT models, estimated probabilities differ. While probabilities in the Black list are almost the same and rich the maximum of 17% in both models, Logit gives much more rosy picture for the best banks, i.e. those from the White list, – the probability of fail is about 10 time smaller than that calculated by AFT. It is worth to note that with AFT estimates of failure probabilities it is hard to find rationale in working with most of Ukrainian banks. For example, for one of the top banks – Nadra bank – to give positive expected payoff for a risk-neutral investor, real interest should be higher than 5.4% per half of the year, while it actually equals about 5.0%[31].

[31] Indeed, on the 22th of May, 2003 Nadra bank offered 13.5% (nominal) interest per year for semiannual deposits, while inflation at April, 2003 was 3.6% (MEMU, May, 2003). However, Logit forecast gives more promising picture – about 40 out of 135 banks have positive expected payoffs.

C h a p t e r   6

DISCUSSION AND CONCLUSIONS

i. Discussion

As can be seen, despite expectations, the hazard model does not perform better than giant logit, even vice-versa – total gain in case of the best logit model (*Table 8, Model 4*) equals 73% and exceeds by 8% that of the best AFT model (*Table 11, Model 2*). Taking into account relative ease of logit estimation, we could conclude that its use is preferable, at least in our particular case. How could this be explained? The core is in underlying assumptions: as was mentioned earlier, hazard model performs well in case of relatively stable environment. This can be clearly seen if we recall that time *t* used in ATF model is not a calendar time, but rather a "living time", *i.e.* the age of the bank. Thus, by using AFT models, we combine different periods of time, mixing together, for example, banks which appeared in 1999 year, and lived for 6 month with those, which born in 2001 and also lives for half a year; and therefore, we implicitly compare banks of different epochs. If the economic situation is stable – this procedure does not make much distortions, and does lead to better results than usual logit (simply by the fact that it uses more information, ceteris paribus). However, taking into account volatile economic situation in Ukraine during 1998-2002, AFT model lead to relatively poorer results. On the other hand, undoubtable gain of using AFT model is the fact that it supports assumption of non-monotonic hazard, by which indicating that the probability to fail reaches its maximum, and the most risky banks are those of about 2.5 years old.

How well do our models work in general? Comparably well. To get a benchmark we can compare them with other studies which use various models for bank failure prediction. However, we should take into account that in general, models for US banking sector (and other Western countries) work better than that for transition ones, mainly because of higher quality data.

Model	Method	Correct Specification, %		
		Failed	*Sound*	*Total*
Pantalone, Platt (1987)	DA	93	97	95
Pantalone, Platt (1987)	Logit	98	92	95
Zmijevski (1984)	Probit	52	100	76
Zmijevski (1984)	Probit	42	100	71
Barth *et al* (1985)	Logit	86	87	86
Hajdu and Virág (1990)	DA	59	54	56
Hajdu and Virág (1990)	Logit	65	61	63
This work: *Model 4*	Logit	80	66	73
This work: *Model 1*	AFT	81	48	65

Source: Hajdu and Virág (1990). DA means Discriminant analysis, AFT – accelerated failure time model.

ii. Conclusion

Significant percentage of problem banks in Ukraine, numerous failures makes it necessary to search for the inner reasons that lead bank toward a bankruptcy. I applied Data Efficiency Analysis with correction for heterogeneity, as well as Giant logit and Accelerated Failure Time analysis with time varying covariates to analyze this issue.

We conclude that on average, dichotomy dependent variable model and accelerated failure time model lead to similar results, predicting with accuracy of about 75% bank's state – either bankrupt or non-bankrupt. One of the major factors that influence the probability and the time to fail is bank's size. All the models support the finding that the bigger is the bank, the less likely it will go bankrupt. Overinvestment into securities seems to be a good indicator of possible problems: the bigger is the share of securities in bank's credit-investment portfolio, the higher is the likelihood of insolvency. Another valuable indicator is the amount of demand deposits in individual deposits; an increase in this ratio also leads to the acceleration of failure probability.

There is evidence that banks located in developed regions and banks that are more profitable are relatively more safe, however, these finding are not supported by duration analysis. On the other hand, duration modeling clearly indicates that managerial efficiency accounts for a bank's soundness: the higher is managerial efficiency, the less likely that a bank will go bankrupt.

Duration analysis reveals that the probability of a bank to fail has a peak: firstly, it grows, and starting from some critical time starts to fall, and thus, in the long run the bigger is the age of a bank, the more safe it is. For an average bank, this critical time equals about 2.5 years. Both managers and regulators can easily evaluate it, as well as timing to failure, for any particular bank and create a required strategy.

Possibility for further research depends mainly on the availability of higher quality data. It would be of interest to investigate the same problem using quarterly data for the whole banks population, which would become possible if National Bank of Ukraine starts to publish official reports. Another interesting possibility would be inclusion of macro variables, which also requires relatively long panels to account for inertia.

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