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1. INTRODUCTION

1.1. The significance of the topic

The economic reform following the change of the social system was a hard hit on the structure of agriculture. During the compensation and privatization processes agricultural enterprises were reformed or disintegrated. A structure of a different approach — that of a private owner has appeared. The changed economic and market relations have presented new challenges for companies.

The bankruptcy act which became effective in the middle of a deep economic recession made the collectability of bank debts uncertain. Among such circumstances the act about financial institutes also becoming effective meanwhile put a great burden on the bank sphere. All this changed the relationship between creditors and debtors, made it more severe; made them realize the importance of debtor rating and rerating.

The relationship between the enterprise and bank may be considered from two viewpoints:

1. the bank and the enterprise as the bank's future client,
2. the bank and the enterprise as the bank's present client.

We may talk about the first case, when the enterprise needs external capital. This might have different reasons: increasing production capacity, temporary crisis, liquidity shortage due to seasonality, etc. The bank examines the possible investment opportunity and depending on the result of the examination the relationship begins or not. We may talk about the second case, when the bank manages the credits in progress or grants new credits meeting the demands of the enterprise and its situation. A very important common step in both cases is the customer or debtor rating. Therefore, the relationship between the bank and the enterprise may be traced back to the prediction of the enterprise's solvency.

In the event of selling or buying on credit or settlement of accounts in final products a short term debtor-creditor relationship (the current liabilities and the trade receivables) is formed, which is not always characterized by contractual payment. To form the deadlines, methods and limits of payment the customer as well as the seller needs the customer rating system. The solvency predictability of their own company and partners is extremely important for the company's management.

The prediction of solvency with statistical methods is not a novelty. It has been applied in crediting in other countries for decades. The bankruptcy models are more and more frequently used in debtor rating systems in Hungary as well. In spite of this these methods are rarely used in enterprise management and not used at all in the agricultural sector. In the author's opinion in the judgment on the solvency of agricultural enterprises the following factors, typifying agriculture, must be considered:

- the Hungarian agriculture suffers from chronic capital shortage, its capital structure differs from other branches,
- the relation of ROE (Return on Equity) and ROD (Return on Debts) in the Hungarian agriculture is reversed compared to other branches,
- the values of liquidity and other rates fluctuate to a grate extent within a year due to seasonality, and their interpretation may change depending on the date of calculation.

Therefore it may be justified to develop new solvency and insolvency prediction models exclusively for the Hungarian agricultural enterprises.

1.2. Targets

The topic of my dissertation is debtor rating, – which is possibly the most important part of the relationship system between agricultural enterprises and banks financing them, – and within that the objective prediction of insolvency with the help of financial ratios.

It is the interest of the financing institute as well as the enterprise to recognize the approach of insolvency early. It is true for the latter even if it is not planning the involvement of (new) outside capital. An **insolvency prediction model** incorporated into management information systems may be an important tool in the hands of the management, as with its help it may trace the changes of the company's solvency depending on the management decisions.

The targets of my research are the following:

1. the analysis of the applicability of multivariable insolvency prediction models in judging the solvency of Hungarian agricultural enterprises through analyzing the insolvency prediction models developed abroad;
2. creating a programmable — feasible in a software format — system of rules for the calculation of financial ratios and the development of models;
3. creating insolvency prediction model(s) especially for Hungarian agricultural enterprises and presenting the possibilities of application.
4. determining which the most important financial ratios are —considering their applicability — in the judgment on solvency of Hungarian agricultural enterprises among the ones formable on the basis of data from the balance and profit and loss statement of the annual report.

2. MATERIAL AND METHOD

2.1. Database

I made a database for my research on the basis of data from the Company registration and information service of the Ministry of Justice. The database contains the 1999 annual balances and profit and loss statements of a sample consisting of 146 companies, operating for minimum one year. For the analyses — for the calculation of financial ratios — I used the closing data of the 1999 year. The sample consists of two parts:

1. 73 insolvent companies;
2. 73 solvent companies.

I selected the companies from the CD VÁLLALATHÍREK[1] (31. May 2001.) database on the basis of the activities summarized in Table 1:

Table 1: Activities of the enterprises constituting the sample

Code of activity[2]:	Meaning of code
EAOR 3	Agriculture and Forestry
TEAOR A	Agriculture, Hunting and Forestry
TEAOR98 A	Agriculture, Hunting and Forestry

I chose the liquidation proceedings initiated against the company in 2000 to be the criterion for a company to be rated as insolvent.

The checking of the results was carried out using the financial ratios calculated on the basis of the closing data of the year 2000 gained from the database containing the 2000 annual balance and profit and loss statements of a **control enterprise sample.** The sample consists of 19 insolvent and 48 solvent companies. During the compilation of the control sample I observed the one year later data at each criterion. The two company samples did not overlap.

2.2. Financial ratios

For my analysis I collected over 60 different financial ratios — calculable from the data of the simplified annual report. The majority of them have been known and applied or prescribed by regulation (14/2001. (III. 9.) FM decree, 9. §) in the practice of crediting (e.g.: quick ratio, current ratio). Theoretically, the automatic calculation of financial ratios is also possible, for instance via dividing, adding, etc. the lines of the annual report with one another. The ratios calculated

[1] ENTERPRISE NEWS
[2] Hungarian Standard Sectoral Classification of Economic Activities

in this manner would not be professionally interpretable but would present an opportunity to discover even absolutely new relations.. The drawback of this approach is the exponentially increasing demand for computer-capacity as the number of ratios increase[3]. I would like to examine the applicability of automatic ratio calculation in my research later; however in the current stage of work I had at least three reasons not to use this „mechanical" solution:

1) one of my targets is to create a model development method applicable with average — **found** in the majority of the offices — computer-capacity;
2) I presuppose, that it is possible to reach adequate reliability with a method demanding less computer-capacity;
3) With the simpler analyses I wanted to form a base for, check the necessity of further, more complicated analyses.

Considering the above I had to resort to a compromise: I tried to include as many as possible known or made by me ratios, which can be professionally interpreted basically. I borrowed some of them from the models of other authors. After that I excluded the ratios which can be linearly generated from other used ratios, to avoid multicollinearity. During the exclusion I carried out tests introducing or omitting the ratios in question (the ones concerned with multicollinearity) one by one. Therefore the ones giving the best results, correlating with the final result the most always remained. I adjusted some ratios in a way that they became easier to handle mathematically.

2.3. Applied analyzing methods

I composed the following principles for the selection of the method to be applied:

1. the method should be suitable to classify cases into two predefined groups,
2. it should take into account more variables at the same time,
3. the results generated by it should be simply interpretable and quantitative,
4. it should be suitable for the reduction of number of the initial data with as little loss of information as possible,
5. it should not be too sensitive to the distribution, deviation, character of the initial data
6. the model resulted in should be easy to handle: should be usable with a spreadsheet application or a calculator, that is it should be flexible and device independent,

[3] The demand for computer-capacity is not an insurmountable obstacle; there are more ways to fulfil it. For example: the *Distributed Analysis* function in SPSS, during which the composition of the calculation task takes place on a local (office) computer, whereas it is executed on a distant server — bearing a much bigger capacity.

7. the analysis with the help of the model should be executable in one cycle (taken off the preparation of the data),
8. to realize the method to be selected the necessary knowledge and material sources should be available.

The discriminant analysis and the logistic regression meet the above requirements the best. There are many more restricting factors to the application of discriminant analysis (see later); however its prevalence and the simplicity of the models created with it recommend it. Therefore I applied the two methods simultaneously.

2.3.1. Logistic regression

Logistic regression is for determining the probability of uncertain categorial result variable's categories under the conditions of other describing variable's known values. Relying on the values of conditional probability the decision maker can construct a decision rule about which predefined result-category (population) he/she classifies a given observation unit into. The number of value of result variables may be two or more. If the number of outputs is two, the method is called *binomial* —in other words *dichotom* — logistic regression. If there are more variables, it is called *polynomial* or *multinomial* logistic regression.

In my dissertation I only deal with binomial logistic regression, as the probability of insolvency, as a prediction problem may have only two outputs: bankruptcy (0), or success (1).The chances of bankruptcy may be increased by certain economic events, the lack of necessary resources to cover liabilities, bad business policy, which lead to the loss of the company's financial balance etc., the effect of which may be detected, concluded with the help financial ratios calculated form data gained from the balance and profit and loss statement of the (simplified) annual report. Consequently, logistic regression is a non-linear classification method which does not presuppose the continuous character of the explanatory variables, thus a multivariable normality either, and with the help of which we may get an answer to the question: from what and how the insolvency of a company depends. There is also an opportunity to present categorial explanatory variables. Using „stepwise" algorithm provides an opportunity to decrease the utmost complete circle of variables causing the supervening of the result (financial ratios), to select explanatory variables on the basis of their significance.

If one output belongs to one observation, and there is an observation belonging to each output, the probability of the $y_i = 1$ output will be π_i, and the probability of the $y_i = 0$ output will be $1 - \pi_i$, then:

$$odds_i = \frac{\pi_i}{1-\pi_i}$$

That is the $odds_i$ is the ratio of the probabilities of solvency and insolvency concerning a given enterprise (i-th observation) According to the supposition of logistic regression the *natural based logarithm of odds* — or otherwise the *logit* of the probability of solvency — is the linear function of the explanatory variables (HAJDU, 2001):

$$\ln\left(odds_i\right) = \text{logit}\left(\pi_i\right) = \beta_0 + \sum_{j=1}^{p} \beta_j x_{ij} \qquad \text{and} \qquad odds_i = \exp\left(\beta_0 + \sum_{j=1}^{p} \beta_j x_{ij}\right)$$

where β_0 is a constant, β_j is the j-th explanatory variable, the coefficient of logistic regression.

Logistic regression has several advantages contrary to other classification methods (for example discriminant analysis):

- it does not have any limitations of any kind about the distribution of explanatory variables,
- in addition to continuous variables (such are the financial ratios —at least within a certain interval) the categorial output variables may also be incorporated into a logistic regression model,
- the values of a logistic regression function may be regarded as probabilities,
- the results are well interpretable.

2.3.2. Discriminant analysis

The discriminant analysis is basically to explain the deviation of different groups according to some kind of variables. Naturally, this explanation is not 100% correct; it may result in „mistaken" classifications. The general form of the linear function (canonical discriminant function) received as the result of the method:

$$Z = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_n x_n,$$

where: β_0 constant,
$\beta_1, \beta_2, \ldots \beta_n$ discriminating coefficients,
$x_1, x_2, \ldots x_n$ independent variables.

If the value of the function is lower than the critical, the enterprise is rated as „insolvent", if it is higher, the enterprise is rated as „solvent".

3. RESULTS

3.1. The preparation of financial ratios

Towards the usability of financial ratios in a model I worked out the calculation method described in this section. The ratios actually are functions with two or possibly three variables, although their variables are very often not independent from one another. Thus, as any other function, they have latent ranges and definition domain. The latent range of some ratio may be $(-\infty; x]$, $[y; +\infty)$ or even $(-\infty; +\infty)$ theoretically, which is often difficult or impossible to interpret professionally. In these cases I corrected some values of ratios belonging to enterprises in more steps:

- in the case of $-\infty$, or values smaller than the 5th percentile, I replaced them by the round-off value of the 5th percentile;
- in the case of $+\infty$, or values bigger than the 95th percentile, I replaced the values over that by the round-off value of the 95th percentile.

I used the values corrected in this manner to build the model. Thanks to this the ratios within the corrected range — apart from a few exceptions — may be regarded as monotonic and continuous functions. Some ratios were omitted from the analyses because their values in certain cases do not characterize the situation unambiguously, or a too complicated condition system is necessary for their software handling. An example for this is the ratio of working capital and equities, which shows the coverage of current assets from the enterprise's own resources. Both the numerator and the denominator of the ratio may be negative, which indicates loss and/or aggressive financing policy. The difficulties in the interpretation emerge when both the numerator and the denominator are negative. Then the value of the ratio is positive and may look very "good", and if we have no other information of the enterprise, the judgment we gave on the basis of the ratio is faulty.

3.2. Experience of the application of two models

I examined the reliability of the models in an empirical way. I tried to classify the enterprises in my company sample with the model on the basis of prepared data. The checking and comparison of results was carried out with the help of a classification table.

The general form of Fulmer's model[4, 5]:

$$\boldsymbol{H} = \mathbf{5{,}528}\boldsymbol{x_1} + \mathbf{0{,}212}\boldsymbol{x_2} + \mathbf{0{,}073}\boldsymbol{x_3} + \mathbf{1{,}270}\boldsymbol{x_4} - \mathbf{0{,}120}\boldsymbol{x_5} + \\ + \mathbf{2{,}335}\boldsymbol{x_6} + \mathbf{0{,}575}\boldsymbol{x_7} + \mathbf{1{,}083}\boldsymbol{x_8} + \mathbf{0{,}894}\boldsymbol{x_9} - \mathbf{3{,}075}$$

where:

$$x_1 = \frac{Retained\ Earning}{Total\ Assets} \qquad x_2 = \frac{Sales}{Total\ Assets}$$

$$x_3 = \frac{Earnings\ Before\ Taxes}{Equity} \qquad x_4 = \frac{Cash\ Flow}{Total\ Debt}$$

$$x_5 = \frac{Debt}{Total\ Assets} \qquad x_6 = \frac{Current\ Liabilities}{Total\ Assets}$$

$$x_7 = \log\left(Tangible\ Total\ Assets\right) \qquad x_8 = \frac{Working\ Capital}{Total\ Debt}$$

$$x_9 = \log\left(\frac{EBIT}{Interest}\right)$$

If $\boldsymbol{H} < 0$, bankruptcy is inevitable. Reliability of the model for a year forward prediction was 98 %, for two years 81 % (FULMER, 1984). The contents of the variables are to be found in the next table.

The general form of Springate's model:

$$\boldsymbol{Z} = \mathbf{1{,}03}\boldsymbol{x_1} + \mathbf{3{,}07}\boldsymbol{x_2} + \mathbf{0{,}66}\boldsymbol{x_3} + \mathbf{0{,}4}\boldsymbol{x_4}$$

where:

$$x_1 = \frac{Working\ Capital}{Total\ Assets} \qquad x_2 = \frac{Earnings\ Before\ Taxes + Interest}{Total\ Assets}$$

$$x_3 = \frac{Earning\ before\ Taxes}{Current\ Liabilities} \qquad x_4 = \frac{Sales}{Total\ Assets}$$

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[4] The last constant of the original formula is not „– 3,075", but „– 6,075". I introduced the modification due to the distortion of the value of the logarithm applied in the calculation of the $\boldsymbol{x_7}$ variable, which was a consequence of filling in the annual report with amounts rounded off to 1000 HUF

[5] *cash-flow = Earnings After Taxes + Deprecation*
EBIT = Earnings Before Taxes + Interest

If the value of ratio Z goes under 0,862, the enterprise is rated as „insolvent". Springate used the data of 40 companies to work out the model and he achieved a 92,5 % reliability.

Table 2: The 1-year forward prediction reliability of foreign models for Hungarian agricultural enterprises

		Fulmer			Springate		
		Predicted STATUS		Correct percentage	Predicted STATUS		Correct percentage
		0	1	%	0	1	%
Observed STATUS	0	48	25	65,7	58	15	79,5
	1	25	48	65,7	44	29	39,7
Overall percentage:				**65,7**			**59,6**

0 = insolvent
1 = solvent

I reiterated the coefficients of the models with discriminant analysis and logistic regression, simultaneously entering all the variables. In some financial ratios the algebraic sign of the coefficient changed in the reiterated models. So, the effect of such ratios in the judgment on solvency of Hungarian agricultural enterprises is reversed compared to western enterprises. For example the ratio of current liabilities — x_6 in Fulmer's model. Having current liabilities is the quickest and cheapest way to improve the profitability of equity. However in the case of Hungarian agricultural enterprises the return of equity is smaller than the return of outside capital, as opposed to other branches or agricultures of other countries Therefore the aggressive financing strategy in Hungarian agriculture generally leads to the increase of liquidity risk and the credit rating becoming worse. The stepwise algorithm executed on the variables of the two models lead to the exclusion of the majority of variables and the improvement of goodness of fit in the cases of both statistical methods. All this confirmed my assumption that it is possible and necessary to develop a new model or models.

3.3. New and novel results

In this section I present the insolvency models developed by me and the results of their application.

3.3.1. Logit-models

The formation of the logistic regression model needed several tests. After analyzing the hits of a preliminary model, I observed that the fitting was better in the case of bigger enterprises. Therefore I formed two smaller sub-samples within the original sample:

1. enterprises with a registered capital not more than 1 million HUF, altogether 49,
2. enterprises with a registered capital more than 1 million HUF, altogether 97.

The following arguments support my grouping system:

- in the case of income- or assets-based approaches the proximity of bankruptcy may distort the judgment on the enterprise,
- the changes of registered capital do not directly depend on the economic activities of the enterprise,
- the registered capital may generally be considered constant within a longer period than assets or income.

Insolvency prediction logit-model for enterprises with a registered capital not bigger than 1 million HUF (Logit 1M)

I worked out the model with logistic regression, with likelihood ratio based forward stepwise algorithm. The structure of the model:

$$\pi = \frac{odds}{1 + odds}$$

where π stands for the probability of the examined company remaining solvent within a year,

$$\ln(odds) = 1{,}950x_1 + 3{,}322x_2 - 0{,}874x_3 - 0{,}698$$

$$x_1 = \frac{Cash\ and\ cash\ equivalents}{Current\ liabilities} \qquad x_2 = \frac{Inventories}{Working\ capital} \qquad x_3 = \frac{Inventories}{Net\ sales}$$

If π is not higher than 0,5 (*cut value* = 0,5) or the value of ln(*odds*) is not positive, the examined enterprise becomes insolvent within a year.

The correct percentage of the model (Table 3) is better than those of the examined two models and that of the model formed with discriminant analysis (see later).

Table 3: The classification table of the Logit 1M model

cut value = 0,5		Predicted STATUS		Correct percentage
		0	1	%
Observed STATUS	0	24	2	92,3
	1	9	14	60,9
Overall percentage:				77,6

With the moderation of entry and removal conditions of variables — *entry probability* = 0,15 and *removal probability* = 0,2 — I tried to improve the fitting of the model by means of including new ratios but the improvement was smaller than expected. I was not able to check the model on a control sample, so a practical application of improved versions is not recommended without further checking, as less significant ratios may be included due to the moderation of variable-selection conditions, and the fitting of the model becomes sample-dependent.

Insolvency prediction logit-model for enterprises with a registered capital more than 1 million HUF (Logit 1M+)

The structure of the model:

$$\pi = \frac{odds}{1+odds}$$

where π is the probability of the examined enterprise remaining solvent within a year,

$$\ln\left(odds\right) = 4{,}649x_1 + 8{,}917x_2 - 0{,}335x_3 - 14{,}71x_4 + 17{,}371x_5 - 0{,}826x_6$$

$$x_1 = \frac{Intangible\ assets}{Non\text{-}current\ assets} \quad x_2 = \frac{Equity}{Total\ assets} \quad x_3 = \frac{Equity}{Authorised\ capital}$$

$$x_4 = \frac{Cash-flow}{Total\ liabilities} \quad x_5 = \frac{Cash-flow}{Current\ liabilities} \quad x_6 = \frac{Inventories}{Net\ sales}$$

If π is not bigger than 0,5 (*cut value* = 0,5) or the value of ln(*odds*) is not positive, the examined enterprise remains solvent within a year.

Table 4: The classification table of the Logit 1M+ logit-model

cut value = 0,5		Predicted STATUS		Correct percentage %
		0	1	
Observed STATUS	0	42	5	89,4
	1	3	47	94,0
Overall percentage:				91,8

The correct percentage (Table 4) of the model is better than that of the previous model. The insolvent enterprises are not recognized more accurately, but the correct classification of solvent enterprises is more than 30% better. From this we might assume that among the „well-operating” small enterprises there are several „bankruptcy-suspicious” ones.

Selecting the Cut Value

According to certain authors the *cut value* should be selected so that the fitting of the logit model is the best. In my opinion, this restricts the opportunities for application by the models giving only „yes – no" (pays –does not pay) type of answers, furthermore it makes the models „sample-dependent". Thus the models will be less usable in rating systems. I think that the selection of *cut value* should not depend on the fitting measured on the given sample, but it should be chosen according to the application target and the circumstances of the model. The essence of this approach is that the *cut value* means the bearable risk in a given situation.

The *cut value* means a critical risk level, so we might regard it as an indifference point where the expected profit and the possible loss are of the same It might depend on more factors, for example the readiness of the decision maker to take risks, the interest rate. According to the principle of rationality, the essential criterion of investment decisions is

value of outputs >value of inputs.

Among risky circumstances the expected values of inputs and outputs are to be used:

expected values of outputs > expected value of inputs .

Starting from this the *cut value* is the π probability, with which the following condition is fulfilled.

$$H \times (k - c)\, \pi = H \times (1 + k) \times (1 - \pi)\ .$$

where H the amount of the credit,
k the interest rate of the credit (% or decimal fraction),
c resource costs (% or decimal fraction),
π the probability of paying back the credit in compliance with contract.

Reordered:

$$\frac{\pi}{1-\pi} = \frac{1+k}{k-c}$$

$$\boldsymbol{\pi = \frac{1+k}{1+2k-c} = \textit{cut value}}\ .$$

The last equation gives the critical risk level on the basis of known interest rate and resource costs. If the level of bearable risk is known (crediting strategy, readiness of decision maker to take risks, etc.), then the minimum interest rate may be determined using the written down relations and with known resource costs:

$$k = \frac{\pi\left(c-1\right)+1}{2\pi-1}$$

3.3.2. Insolvency-prediction models elaborated with discriminant analysis

A model elaborated on a sample with registered capital not bigger than 1 million HUF (DAN 1M)

The general form of the model: $\boldsymbol{Z = 0{,}710x_1 + 1{,}034x_2 - 0{,}412}$

where: $x_1 = \dfrac{\textit{Cash and Cash Equivalents}}{\textit{Current Liabilities}}$ $\quad x_2 = \dfrac{\textit{Inventories}}{\textit{Working Capital}}$

If the value of Z is not positive, the examined enterprise becomes insolvent within one year. The fitting of the model is shown in the following table.

Table 5.
The goodness of fit of the DAN 1M model

		Correct percentage %
STATUS	0	92,3
	1	52,2
Overall percentage		73,5
leave-one-out		73,5

The original correct percentage of the model is the same as the one calculated with the leave-one-out method, however the model rather recognizes insolvent enterprises (Table 5).The recognition of solvent ones is hardly better than random. The model uses only two ratios, so I tried to include new variables with the moderation of entry and removal conditions. However I could not check the operation of the model on the control sample, moreover, the results of its application may only be considered as an indicator because of the asymmetry of fitting. In accordance with this during comparison with logit-models I used the original version of the DAN 1M model and I only present the other versions in my dissertation.

The goodness of fit of the model is worse than that of the logit-model elaborated for the same sub-sample (Logit 1M).

A model elaborated on a sample with registered capital bigger than 1 million HUF (DAN 1M+)

$$Z = 0{,}425x_1 + 0{,}958x_2 + 3{,}25x_3 - 0{,}211x_4 - 0{,}237$$

where:

$$x_1 = \frac{equity}{liabilities} \qquad x_2 = \frac{Earnings\ After\ Taxes}{Total\ Assets} \qquad x_3 = \frac{Cash - flow}{Equity} \qquad x_4 = \frac{Inventories}{Sales}$$

If the value of Z is not positive, the examined enterprise becomes insolvent within a year.

Table 6: The classification table of the model elaborated with discriminant analysis

		Original			Leave-one-out		
		Predicted STATUS		Correct percentage	Predicted STATUS		Correct percentage
		0	1	%	0	1	%
Observed STATUS	0	42	5	89,4	41	6	87,2
	1	11	39	78	11	39	78
Overall percentage:				83,5			82,5

The model shows a better fitting than the examined foreign models, but worse than the logit-model elaborated on the same sub-sample. Its correct percentage (Table 6) is better than the reliability published in similar — but not about models developed for agricultural enterprises — domestic and foreign papers. (VIRÁG 1996, HERRITY 1999, HEINE 2000).

3.3.3. Control

The control sample consisted of enterprises with a registered capital of one million HUF or more. Therefore I could only test the models elaborated with discriminant analysis (DAN) and the Logit 1M+ models. Both models recognize **insolvent** enterprises to the same extent in the sample of 1999 and the control sample (Table 7). The logit model recognizes the **solvent** enterprises approximately to the same extent in both samples. So, the goodness of fit of the logit model is practically the same in the cases of both samples. The goodness of fit of the DAN 1M+ is better for the control sample than for the 1999 sample as a consequence of better recognizing solvent companies.

Table 7: The comparison of the goodness of fits of the models

		DAN 1M	DAN 1M+		Logit 1M*	Logit 1M+*	
		1999	1999	2000**	1999	1999	2000*
STATUS	0	92,3	89,4	89,5	92,3	89,4	89,5
	1	52,3	78,0	87,5	60,9	94,0	93,8
Overall percentage:		73,5	83,5	88,1	77,6	91,8	92,5

* cut value = 0,5   ** control sample

Its overall percentage is better, but altogether it is worse in the case of both samples than that of the logit model. The fitting of the discriminant analysis model for enterprises with a registered capital not bigger than one million HUF is worse than that of the logit model elaborated on the same sample.

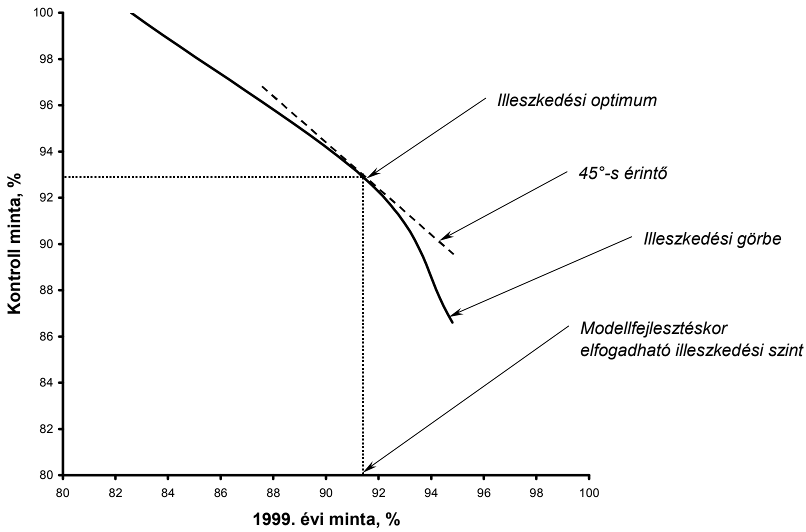

Figure 1: The optimal goodness of fit of the logit model

During the elaboration of the logit-model I was able to improve the goodness of fit of the model for the 1999 sample to over 95% by entering new variables. However, the fitting for the control sample decreased when I did so. I experienced the same if I elaborated a model on the control sample and I tested it on the 1999 sample: the model's fitting could be as good as 100%, but during checking it on the 1999 sample it was hardly more than 82%. Recording these in a coordinate system (Figure 1) it is possible to determine the optimal level of goodness of fit. The line I named "goodness-of-fit curve" represents the relations between correct percentages calculated on the samples used for the elaboration and the checking of the samples. The Logit 1M+ model approaches the optimal fitting level determined with the method illustrated in the above figure.

3.3.4. The selected financial ratios

Table 8: The financial ratios selected by the elaborated models

Variable	Formula	Category	DAN 1M		DAN 1M+		Logit 1M		Logit 1M+	
			Stand. coeff..	Importance	Stand. coeff..	Importance	Stand. coeff..	Importance	Stand. coeff..	Importance
var5	$\frac{intangible\ assets}{non-current\ assets}$	A							0,485	5.
var10	$\frac{equity}{total\ assets}$	C							5,575	3.
var16	$\frac{equity}{authorized\ capital}$	C							-0,365	6.
var18	$\frac{equity}{total\ liabilities}$	C			0,676	1.				
var23	$\frac{cash\ and\ cash\ equivalents}{current\ liabilities}$	L	0,725	1.			2,130	2.		
var25	$\frac{inventories}{working\ capital}$	L	0,704	2.			2,407	1.		
var28	$\frac{earning\ after\ taxes}{total\ assets}$	P			0,481	3.				
var36	$\frac{cash-flow}{equity}$	P			0,524	2.				
var37	$\frac{cash-flow}{total\ liabilities}$	P							-8,364	2.
var39	$\frac{cash-flow}{current\ liabilities}$	P (L)							11,928	1.
var45	$\frac{inventories}{sales}$	E			-0,333	4.	-1,516	3.	-0,817	4.

A = assets structure C = capital structure L = liquidity
P = profitability E = efficiency

Table 8 the financial ratios selected by the four models — DAN 1M, DAN 1M+, Logit 1M and Logit 1M+ logit — and their order of importance on the basis of the coefficients of models edited on standardized ratios (Stand. coeff.). Inside the models with several variables, the interactions of variables also have effects, the variables in the model influence the judgment on solvency, not the solvency itself. That is they reflect the situation but do not explain it. They represent the effect in the causality relation, so the discovery of the causes is possible via analyzing the formed situation, for which further analyses — not targets of this dissertation — are often necessary.

In the case of case of enterprises with a registered capital not more than one million HUF the two statistical methods selected the same variables— *var23* and *var25* — into the models. Therefore in the judgment on solvency of small agricultural enterprises the liquidity ratios are the more important. The positive algebraic signs of the coefficients of *var23* and *var25* — *cash liquidity* and *tying up of working capital* — indicate a high ratio of current liabilities. The third variable of the Logit 1M model, the one called *var45* — *inventory/sales* — appears in one of the versions of DAN 1M, furthermore in the insolvency prediction models for bigger enterprises, uniformly with a coefficient with a negative algebraic sign. The following may cause the increase of the value of the variable:

- sales problems: the enterprise does not get enough revenue due to unfavorable purchasing prices and forms a too big inventory;
- the enterprise does not produce a satisfactory quantity of **realizable** finished products.

The judgment on the ratios in the DAN 1M model meets the general expectations, however the variables of the Logit 1M+ model need some explanation. The negative algebraic sign of the coefficient of the profitability ratio called *var37* (*cash-flow/outside capital*) is the consequence of the high ratio of current liabilities, as the next variable in the model — *var39* — has a positive effect, its numerator is the same and there are only current liabilities in its denominator. The two ratios indirectly indicate the low profitability of equities. The big coefficient of *var10* (*equities/total sources*) in the standardized model emphasizes the importance of capital supply of agricultural enterprises. The *var5* (*intangible assets/ invested assets*) is in the Logit 1M+ model, which indicates the professionalism of the management, the business administration policy and successfulness of the enterprise, since its numerator contains the following: contractual or other legal rights, goodwill, intellectual products (patent, know-how), experimental developments and the activated value of establishment and reorganization. The negative algebraic sign of the coefficient of the least significant variable *var16* may be explained by the latent relations among ratios, as it did not turn out unambiguously from the distribution of values of ratios. The removal of the ratio from the model did not have an effect on the fitting checked on the control sample.

4. CONCLUSIONS AND RECOMMENDATIONS

On the basis of the results of the executed analyses I proved that the insolvency of Hungarian agricultural enterprises may be predicted on the basis of data obtained from the balance and profit and loss statement of the annual report and the simplified annual report with multivariable statistical methods. The reliability is not worse than in the cases of models developed for enterprises of other sectors, countries. My results confirm the raison d'ętre of prediction models elaborated with discriminant analysis and logistic regression, as besides the good reliability of the rating of agricultural enterprises according to financial risks a further advantage of the models is taking more significant factors into account at the same time and the exercise of interactions among factors. The application of logit-models modifies the circumstances of financing decisions from uncertain to risky. Thereby the financing of agricultural enterprises becomes easier to plan.

I examined two foreign insolvency prediction models. Their reliability is far lower than the values measured in their original economic environment. In my opinion this maybe for several reasons:

1. Originally the values were recorded in US or Canadian dollars. It does not cause problems in simple ratios, but does cause problems in logarithm calculations. The problem is not fully eliminated by conversion into dollars either.
2. In balance and profit and loss statements made according to the Hungarian accounting system the values are given in thousand HUF, so the logarithm calculation had to be corrected if the argument was not a ratio but an amount. As a consequence of this in the cases of values between zero and one thousand HUF the continuity of the ratio ceases, which may distort the results of the models elaborated with discriminant analysis.
3. The relations of Hungarian agriculture differ from economic relations in the US and Canada.
4. Mainly in the case of smaller domestic agricultural enterprises the regulating measures due to economic difficulties may obtain a social character, which distorts the market circumstances.

On the basis of the results I do not recommend the application of foreign models in an unchanged form. The reiteration of the coefficients of the models brought some improvement but the revision of the variables included in the models with stepwise algorithm was much more effective It turned out that the interpretations, effects of some financial ratios on solvency in the case of Hungarian agricultural enterprises are contrary to those experienced at American and Canadian enterprises. Moreover due to the special character of capital profitability and capital supply of Hungarian agriculture the interpretations of several ratios need a special approach. All these justified the development of my own specific model.

During processing the balances and profit and loss statements I received a lot of outstanding, uninterpretable values, which were impossible to handle with software. As the first step of checking the two foreign models and developing my model I formed the regulation system of the calculation of financial ratios practicable with software. With its help the original values of the ratios, become easy to handle with statistical software with distortions as small as possible from the point of view of the final result. Further rules of calculation can be formed, following the pattern of the condition system, for the introduction of new variables, this way it is applicable for the development of other models as well.

During the elaboration of my own models I made the following statements:

- logistic regression has proved to be more flexible and accurate method in comparison with discriminant analysis;
- logistic regression is less sensitive to the character of the data, so categorial variables can also be included in the model thereby non-financial and other non-quantitative factors may be taken into account.
- the result of the logit-model is the probability of solvency in one, so it is more widely applicable.
- over the reliability level I called optimal fitting level models become sample-dependent due to the fuzzy character of agriculture, their fitting calculated on the control sample becomes worse;
- the optimal fitting of the logit-model in the case of agricultural enterprises with a registered capital bigger than one million HUF is 91–93 %.

In accordance with the above I recommend logit models for practical applications, among them the **Logit 1M+** model, as I could only check the models of bigger enterprises on a control sample. The application of the Logit 1M model may be only conditional and needs further analyses.

The usage of the model is somewhat different in company management and in commercial banks or in investors' environment:

Company management

- Early Warning System
- A tool of decision-making support
- A part of management information systems
- A part of a simulation system
- Partner-rating (limits, conditions of payment)

Investors' environment:

- a preliminary rating tool in the annual and more frequent (quick) rerating of already existing clients,
- a determining credit conditions,
- development and control of scoring systems,
- insolvency function in the already operating debtor-rating systems.

By making more interim balances and profit and loss statements the prediction may be safer and more dynamic. The cash-flow of agricultural enterprises changes very characteristically cyclically, the solvency changes with it so the bigger than usual (negative) changes may be recognized earlier with the help of the model's values calculated on the basis of interim balances. The place of the logit-model in integrated control systems is illustrated in Figure 2.

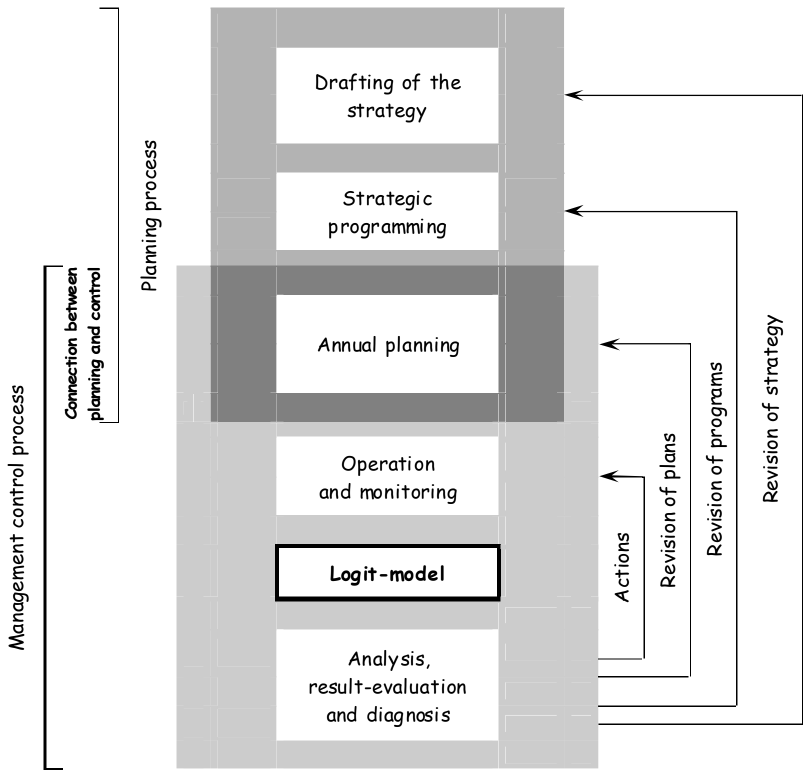

Figure 2: The place of the logit-model in the integrated system of planning and management control processes

based on SZÉKELY (2000)

It may be the target of **further research** to define the domains within which the changes of financial and other characteristics during a financial year are still admissible from the point of view of solvency. The insolvency prediction model may prove a useful tool of such research. If the target is not the development of a model, with the help of logistic regression we can discover the latent relations among ratios characteristic for the given sample — group of enterprises. To achieve this we introduce different ratios into the model with the Enter method or by providing a basis for further research through moderating entry conditions

The determining and control of **credit conditions** according to risks is illustrated in Figure 3, presupposing that the amount of the credit remains under the given credit limit. The utility function illustrates the risk-taking and financial strategy of the bank. Credit accommodation is only possible with conditions enclosed by the two curves — a grey area in the figure.

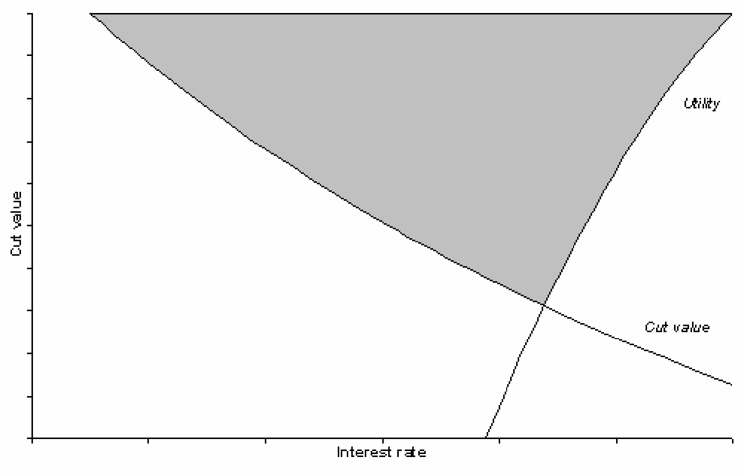

Figure 3: The determination of credit conditions with the help of the logit-model and the utility function

From the goodness of fit of the models I developed and the distribution of hits I made the following statements:

- for the insolvency judgment on smaller enterprises the models selected relatively few —two, or three — ratios;
- the insolvency and solvency prediction of enterprises with a registered capital not bigger than one million HUF is less accurate than that of bigger enterprises;
- the models developed with both statistical methods recognized the insolvent enterprises in the sub-sample of smaller enterprises much better than solvent ones.

From the above I came to the following conclusions:

- for the safer solvency judgment on smaller enterprises it is necessary to take further —non financial (personal background, production structure) factors into account.
- it is necessary to develop models for different enterprise sizes;
- probably many more smaller enterprises operate on the edge of bankruptcy, than those against which liquidation proceedings or bankruptcy

proceedings are initiated, their subsistence may be explained by „non market" tools;

In the reiterated foreign models as well as in the model I developed the interpretation of the coefficients of variables — ratios — may originate from the special characteristics of Hungarian agriculture: unfavorable capital supply and structure, unfavorable profitability of capital, a high ratio of yields distributed not as goods.

Therefore the insolvency model elaborated with logistic regression can be applied not necessarily when taking up and accommodating credits. Similar information may be necessary for the management when working out the strategy, the owners and the potential customers when selling the whole company or some share of the business etc. Furthermore the model can be used as a tool of research, the results of its application may serve as a basis for further analyses.

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Keywords: Фулмер, Fulmer, Спрингейт, Springate, модель, неплатеж.