PORTFOLIO SENSITIVITY MODEL FOR ANALYZING CREDIT RISK CAUSED BY STRUCTURAL AND MACROECONOMIC CHANGES

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Professional Article**
UDC 657.92(035)
JEL G21

Abstract

This paper proposes a new model for portfolio sensitivity analysis. The model is suitable for decision support in financial institutions, specifically for portfolio planning and portfolio management. The basic advantage of the model is the ability to create simulations for credit risk predictions in cases when we virtually change portfolio structure and/or macroeconomic factors. The model takes a holistic approach to portfolio management consolidating all organizational segments in the process such as marketing, retail and risk.

Keywords: portfolio analysis, credit risk, weighting, scoring, data mining, sensitivity analyses, decision support, Bayesian networks, BASEL II

1 Introduction

High-quality portfolio credit risk management is a crucial element of financial institutions and their functioning. From a credit risk perspective, the main goal of an ideal portfolio management is to keep the credit risk at a level to maintain at least the same financial results, or to accept higher credit risk for adequate better financial results.

The main goal is to acquire such clients (and "sell" them such type of products) that the marginal contribution of these new clients to the entire portfolio risk is minimized. There is always a possibility of increasing the risk in a portfolio because of changed bu-

* The author would like to express his gratitude to the three reviewers for their suggestions and comments.
** *Received*: June 1, 2008
Accepted: December 16, 2008

siness or market conditions or deterioration in the debtor's risk profile and these changes can cause business loss.

There are numerous papers which are focused on credit risk modeling (Muromachi, 2004; Andrade and Sicsú, 2005; Madhur and Thomas, 2007; Mihail, Cetină and Orzan, 2007). Some solutions depict a dominant use of one statistical method, such as the Cox Proportional Hazard Model (Madhur and Thomas, 2007), or the use of a statistical distribution which best fits the credit loss in each portfolio segment (Andrade and Sicsú, 2005). Various papers approach the mentioned problem from a national economy perspective (Andrade, 2005), while some take into account macroeconomic factors as well as potentially very interesting factors in portfolio risk evaluation (Madhur and Thomas, 2007). Mihail proposes a model for credit risk evaluation (Mihail, Cetină and Orzan, 2007).

Both portfolio structure and potential portfolio risk are directly connected with strategic business decisions which cause the portfolio to expand. The fact that market conditions and macroeconomic factors can increase or decrease the risk of the existing portfolio cannot be neglected. This means that we can manage the portfolio risk by making strategic business decisions about which market segments we should target with new campaigns. On the other hand, the existing portfolio can show some performance on risk regarding various macroeconomic changes, which also means that newcomers (new users of a risky product) can also show a performance on risk regarding certain macroeconomic changes in the future. New campaigns and new clients surely change the global portfolio structure. After the changes in this structure, the portfolio can exhibit different behavior characteristics regarding macroeconomic changes.

All this leads us to a question: how to simulate all those processes and how to make a decision support system/model which can cover all these situations? The above mentioned papers do not give us a solution covering all the topics with a general solution serving as a decision support system/model. Managers often make decisions in conditions of uncertainty and it can therefore be helpful to simulate the consequences of business decisions, taking into account the present portfolio structure and sensitivity to macroeconomic changes with some statistical certainty. For example, during the phase of campaign planning it is useful to know whether the risk increases or decreases if we target some specific population instead of only using an educated guess.

All the mentioned facts lead us to a conclusion that the system/model for simulating the consequences of business decisions regarding risk is useful for portfolio credit risk management. This model should follow recent changes in portfolio and take it into consideration in the next simulation cycle. As mentioned above, the model has an influence on strategic planning, which means that it has a consolidation role, the simulation resulting in business decisions which are closely related to marketing and retail activities, applying the simulation results in marketing retail/SME activity, etc.

The aim of the article is to show the synergy of using credit scoring techniques and weighting techniques for a portfolio credit risk simulation. We will show the theoretical background of the solution, which consists of the scoring model and weighting techniques, and demonstrate the solution with public data using the mentioned models and Bayesian networks.

2 Theoretical background

2.1 The basics of portfolio sensitivity model

Portfolio credit risk will be considered as unlikeness to pay. This means estimating which customers will be in default and which will not. For this purpose, application scorecards and behavior scorecards can be used. The application scorecards are used to evaluate the potential risk of new customers who should become a part of the portfolio. Regarding this, we define a cut-off score which is a judgmental factor for a decision whether we should approve some risky product to a customer or not. The behavior scorecards are used for a probability of default evaluation for existing customers in a portfolio for a fixed future period of time (BCBS, 2004).

That means that we use the application scorecard in a process of approving some risky product, and we use the behavior scorecard for the risk evaluation of the existing users of a risky product after the approval process when they are in our portfolio.

The probability of default in our model is the basic evaluation measure which could be extended on other profitability measures or RWA (Risk Weighted Assets) calculations.

The application and behavior scorecards are the bases for the proposed risk evaluation model based on probability of default.

The basic idea is to apply the scorecard models to a weighted portfolio. Weights could be based on risky factors recognized through the process of univariate analysis which detects the key risk factors, being a common procedure in a scorecard development. Weights could also be constructed by means of risky macroeconomic factors. We should distinguish application factors from behavioral factors regarding the two types of used scorecards.

This means that if we analyze the consequences for the portfolio risk in the case of making a strategic decision to increase our portfolio by 1000 new clients who belong to a younger population from some district, we will use the application scorecard on a weighted portfolio. On the other hand, if we want to analyze the consequences of the oil price increase and devaluation for portfolio risk we will use the behavior scorecard on a weighted portfolio.

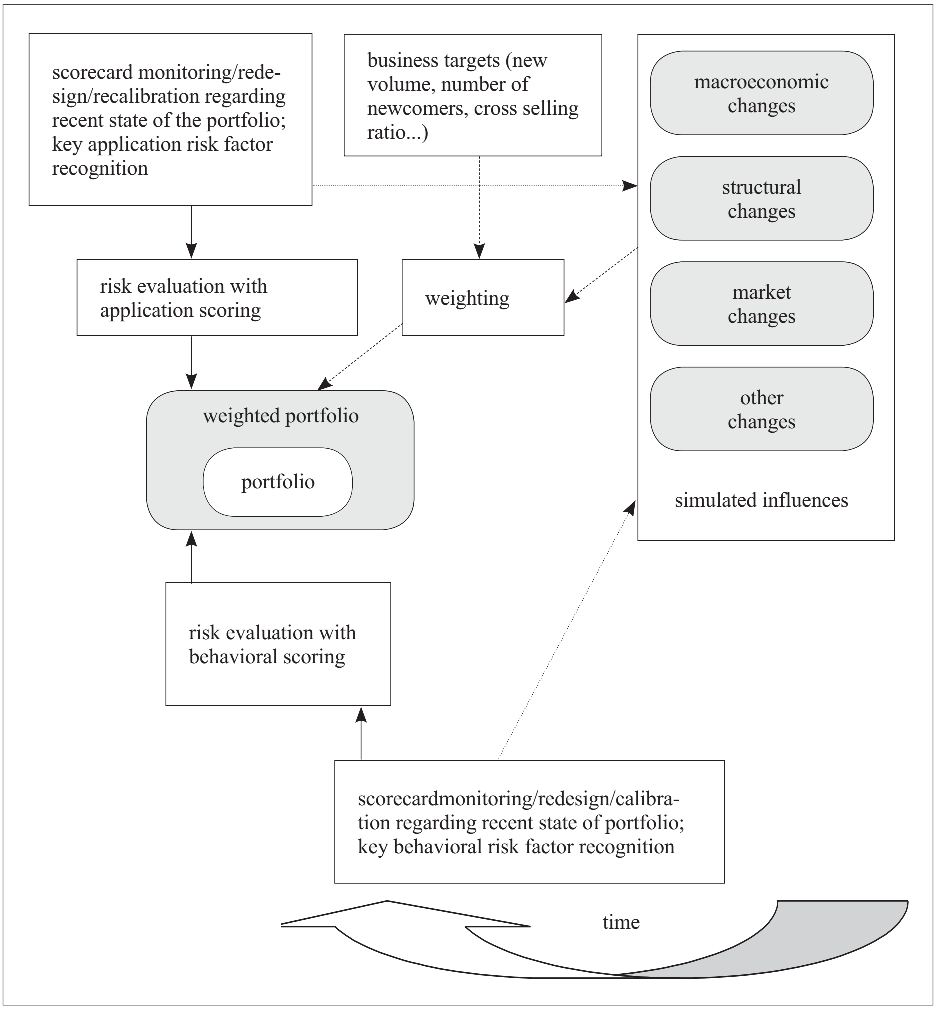
The fact is that the portfolio should not be sensitive or significantly sensitive to all potential structural or macroeconomic changes. Which factor has the greatest impact on portfolio sensitivity should be determined through the process of univariate analysis.

We can also use both scorecards on a weighted portfolio if we want to analyze the consequences for the portfolio risk of a strategic decision to increase our portfolio by 3000 new clients who belong to a younger population from some district and under the condition of oil price increase and devaluation.

As time passes, the portfolio becomes much more mature, and it can change its own risk characteristics. This means that some factors which have been recognized as significant for risk evaluation might lose their relevance for a certain period of time, because of new client acquisitions. The structural changes in the portfolio bring us some new significant risk factors.

New portfolio characteristics which have a great influence on the portfolio risk performance could be recognized through periodical scorecards monitoring and recalibrations. These characteristics are a basis for the observed portfolio sensitivity model. Characteristics which have no significant impact on the portfolio risk could be excluded from a detailed observation of the portfolio sensitivity model. Figure 1 shows the basic structure of a proposed portfolio sensitivity model with the mentioned characteristics. This is a cyclical process with a synergy effect which is time dependent.

Figure 1 Basic structure of proposed portfolio sensitivity model



Source: author

2.2 Using credit scoring models

Scoring models play a central role in the model. Usually, scorecard models are based on logistic regression which is shown in equations (1) and (2) (Norušis, 1999).

$$P = \frac{e^z}{1+e^z} \tag{1}$$

Z is the linear combination of independent variables.

$$Z = \beta_0 + \beta_1 X_a + \beta_2 X_2 + ... + \beta_n X_n \tag{2}$$

Independent variables which we selected in the model are chosen during the attribute relevance analysis (univariate analysis). These variables satisfy the criteria of highest default prediction power. This means that independent variables could be used in the sensitivity analysis too. It is important to stress the possibility that some of the variables with high default prediction power could be excluded from the model, because of a high correlation with some of the variables within the scoring model. These variables can be included into the sensitivity analysis through Bayesian networks.

Instead of a logistic regression, we can use neural networks, decision trees, or other methods for scorecard modeling, which could also be used in the model for sensitivity analysis.

A big contribution of scorecard models to portfolio sensitivity modeling is the use of univariate analysis results from the scorecard development process.

This result shows us the potential of independent variables for probability of default prediction.

2.3 Weighting process

Portfolio observation could be done based on the present or past portfolio state, in which we take into consideration the real present or past portfolio situation. This approach gives us no opportunity to make a *what if* analysis. It is important for a business to evaluate the future consequences of present business decisions. This means that managers should have an opportunity to reduce uncertainty during the decision making process. Uncertainty can be reduced by analyzing the current and the past portfolio state, but a much more precise approach would be to apply a *what if* analysis of the portfolio. This can be done by using weights on the current portfolio. Weights have influence on the portfolio volume and the change in portfolio structure. In case we discover several crucial factors (during the process of univariate analysis) which have a great influence on the portfolio risk, we can make *what if* scenarios using weights. This means that we could virtually increase the portfolio volume by portfolio members that have risky characteristics. We can also make *what if* scenarios by changing a portfolio structure in which risky parameters have a greater influence on the same portfolio volume.

These two approaches depend on the final aim of the analysis /business decision.

If we want to know, for example in case of a new marketing campaign aimed at attracting new portfolio members (clients) from some district, and increasing the portfolio volume by 5%, how risk parameters will change in the future if we have a great devaluation, we will use weights which will virtually increase the portfolio volume by 5%, together with increasing the number of portfolio members with the described characteristics. If we want to know, for example, how different portfolio structures of the same portfolio volume would influence the portfolio risk (e.g. predominantly younger population with low income) we will use weights for changing the portfolio structure.

Originally, weighting techniques were used for correcting survey errors, when the respondent sample did not represent population well (Sarraf & Chen, 2007). Our basic idea is to represent the projected portfolio population in the future as population in surveys, which leads us to applying the weighting techniques.

For the mentioned purposes we could use two types of weighting techniques (Sarraf and Chen, 2007; Maletta, 2006):

Scale weight calculation

$$w_i = \frac{P_i}{R_i} \tag{3}$$

where w_i is the scale weight, P_i is the population subgroup count regarding i, R_i is the respondent subgroup count regarding i, and i is the subgroup index.

Proportional weight calculation

$$w_p = \frac{\textit{percent of population}}{\textit{percent of respondents}} = \frac{\frac{P_i}{P_{total}}}{\frac{R_i}{R_{total}}} \tag{4}$$

where w_p is the proportional weight, P_i is the population subgroup count regarding i, R_i is the respondent subgroup count regarding i, P_{total} is the total number of members in population, R_{total} is the total number of respondents, and i is the subgroup index.

The scale weight will be used if we want to measure the effects of structural and volume changes in the portfolio.

The proportional weight will be used in the cases when we want to measure the effects of structural changes on the same portfolio volume.

2.4 The role of Bayesian networks

Weighting can be used in the cases when we want to monitor changes in the portfolio caused by changes in just a few critical variables. If we want to monitor the changes in the portfolio caused by changes in more than just a few variables (e.g. five or more), it is very hard to make a scenario analysis using weighting. This is possible, but very inconvenient and difficult. In such a case we can use Bayesian networks.

Bayesian networks are based on conditional probability, and they demand expert knowledge of the business area for constructing links between variables. “Bayesian networks specify joint conditional probability distributions” (Han, 2001).

Bayesian networks are graphically represented as linked nodes consisting of conditional probability tables. A Bayesian network calculates joint probabilities regarding a created model.

Bayesian networks can be applied for risk measuring when we have a synergy effect of variable influences, due to variation in a great number of variables.

From the experience point of view, the described weighting techniques could be sufficient for these purposes, because we already know through a univariate analysis which variables have the biggest influence on the portfolio credit risk. It is often not more than four variables, which could be covered by the proposed weighting model. Sometimes, if we want to construct a complex model integrating several macroeconomic factors, key variables recognized through the univariate analysis, it is better to use Bayesian networks. The reasons for that lie in the fact that Bayesian networks are much more powerful to follow the synergy between variables than logistic regression, and Bayesian network models have modules for sensitivity analysis when we change probability states of several variables.

2.5 Expected outputs

A decision maker wants precise and understandable information which is a milestone for the right decision. Regarding this, the analysis results should be organized in a way that shows predicted causes of potential business decisions.

The proposed model gives these opportunities, because the expected output from the model can be presented in the *what if* forms (e.g. if portfolio expands by 6% by including middle aged population living in a district X, we can expect an increase in risky trends (defaults) by 0.8%).

Another important thing is that we can also calculate profitability and possible loss caused by increasing the portfolio by a risky population, which shows that we can cover losses by increased profit.

The model could also take into consideration macroeconomic factors like oil price increase, devaluation, etc. In that case, a decision maker could foresee the percentage of increase in risky trends (defaults), if devaluation and/or oil price increase are to be expected and we want to increase the portfolio volume by 7% by including younger population.

3 Testing the hypothesis on public data

3.1 Data set description

We use the testing data set from the book *Credit Scoring and Its Applications* (Thomas, Edelman and Crook, 2002)

Table 1 shows a data dictionary used from the book *"Credit Scoring and Its Applications"*.

Table 1 Description of used data

Variable Name	Description	Codings
age	year of birth (used for age calculation)	If unknown, the year will be 99
nkid	number of children	number
Dep	number of other dependents	number
phon	is there a home phone	1 = yes, 0 = no
sinc	spouse's income	
Aes	applicant's employment status	V = government W = housewife M = military P = private sector B = public sector R = retired E = self employed T = student U = unemployed N = others Z = no response
dainc	applicant's income	0 means no income or client did not give information about income
Res	residential status	O = owner F = tenant furnished U = tenant Unfurnished P = with parents N = other Z = no response
dhval	value of Home	0 = no response or not owner 000001 = zero value blank = no response
dmort	mortgage balance outstanding	0 = no response or not owner 000001 = zero balance blank = no response
doutm	outgoings on mortgage or rent	
doutl	outgoings on Loans	
douthp	outgoings on Hire Purchase	
doutcc	outgoings on credit cards	
bad	good/bad indicator	1 = bad 0 = good

Source: Thomas, Edelman and Crook (2002).

In the first step, data characteristic was analyzed using descriptive statistic. As mentioned by the authors (Thomas, Edelman and Crook, 2002), the prepared data set was altered but there was no missing data caused by bad data quality.

The data set in the book has the role of a data sample for credit scoring development. In our case the data set is used as portfolio data on which portfolio sensitivity analysis will be applied. This sample will first be used for the application of (bank) credit scoring.

3.2 Credit scoring model development

The data set was first used for credit scoring model development. As a result of univariate analysis, we got Information Values (IV) for each attribute in the sample.

Table 2 shows the prediction power for each variable in the sample regarding good/bad indicator (default prediction).

Table 2 Information value table

Attribute	Information Value
Age	0.287000000
dainc	0.267672156
Aes	0.176406850
doutcc	0.090116714
doutm	0.078226250
Res	0.059269664
dmort	0.039024278
sinc	0.029209627
douthp	0.023617316
doutl	0.022905496
dhval	0.018834036
phon	0.009115428
Dep	0.003923339
nkid	0.001700000

Source: author's calculation.

Taking into consideration information values, we have a pretty good picture of portfolio sensibility and key risk indicators. Attributes which play a major role in the default prediction are attributes with highest information values in the sample. These variables are the key variables for portfolio sensitivity model development. Variables with highest information values have the biggest impact on portfolio risk.

In the information value calculation we could also include macroeconomic variables, seasonal oscillations (Klepac, 2007), and other behavioral variables, if we develop a behavior scorecard model.

The information value shows us which variables are convenient for portfolio sensitivity evaluation. Variables with low information values have a very weak influence on portfolio risk and, theoretically, they do not play an important role in increasing the portfolio credit risk.

When trying to make a prediction through the model, we should concentrate on variables with high information values.

After the creation of a dummy variable and applying a correlation analysis of the data, a scoring model was created using binomial logistic regression (1) (2).

The final scoring model is shown in *Table 3.*

Table 3 Scoring model

Coefficients (Binomial logistic regression)	**B**
applicant's income 1 - 12000 $	-.076
applicant's income 12001 - 34650 $	.151
applicant's employment status (W,R,Z,U)	-.815
outgoings on credit cards 1 - 200 $	.368
outgoings on credit cards > 201 $	1.397
age 36 - 65	.309
constant	.806

Source: author's calculation

The scoring model is important in the last phase of portfolio risk evaluation. In the current phase, weights have an influence on good/bad indicator and we do not need a scoring function. In the later phase (especially for behavioral scoring), when we have to predict who will go into default with highest probability, we need a scoring model. After applying the scoring function on the data sample, the next step includes the use of weighting techniques for the sensitivity analysis of credit risk.

3.3 The use of weighting

A univariate analysis shows which attributes are the most relevant for default prediction. This implies that significant changes in portfolio structure regarding attributes with the highest information values would surely have an impact on portfolio credit risk.

Two most significant attributes in the used sample are age and applicant's income. During the univariate analysis, we recognized significant subgroups within attributes (it is a common procedure during scorecard development).

Let's suppose that we would like to investigate our portfolio regarding two most significant attributes having the biggest influence on portfolio credit risk. It could be done by using cross tabulation between mentioned variables regarding the recognized significant subgroups within variables. The result of the conducted analysis is shown in Table 4.

Table 4 Cross tabulation of data sample by applicant's income and age

		Applicant's income (US$)			
		< = 0	**1 – 12,000**	**12,001 – 34,650**	**34,651+**
Age	< = 35	68	28	85	27
	36 – 65	74	79	460	217
	66+	64	59	63	1

Source: author's calculation.

Let's suppose that we plan an acquisition of new clients and we would like to target potential clients, taking into consideration an increase in overall volume of portfolio, but also increase in the number of members of observed subgroups in the portfolio. As we know that, in our case, the applicant's income and age have the biggest influence on portfolio credit risk, we can make an assumption of a portfolio volume increase by approximately 55% (676 new clients). We would like to know whether the portfolio credit risk will be lower or higher if marketing campaign would be targeted on specific segments (see bold values in Table 5; bold values mean changes in the portfolio).

Italic values in Table 5 mean planned new values of portfolio segments. It is important to have in mind that we calculate the portfolio credit risk for the period used in the observation window during the scorecard development. It is usually one year. It means that we make a simulation to answer the question: "Will new clients (676 of them in our case), who become portfolio members today," go into default during one year (length of credit scoring observation period)?

Table 5 Cross tabulation of aimed population by applicant's income and age

		Applicant's income (US$)			
		< = 0	**1 – 12,000**	**12,001 – 34,650**	**34,651 +**
Age	< = 35	68	*56*	85	*54*
	36 – 65	*74*	*237*	*920*	217
	66+	64	59	63	*4*

Source: author's calculation.

If we want to answer that question, we have to apply weights on the existing data sample (portfolio). In case we are interested in measuring risk parameters after increasing the portfolio volume by altered portfolio structure we calculate the scale weights.

Applying the formula (3) on Table 4 and Table 5, we can calculate the scale weights shown in Table 6.

Table 6 Scale weights

		Applicant's income (US$)			
		< = 0	**1 – 12,000**	**12,001 – 34,650**	**34,651+**
Age	< = 35	1	2	1	2
	36 – 65	1	3	2	1
	66+	1	1	1	4

Source: author's calculation.

In case we are interested in measuring risk parameters without increasing the portfolio volume, and we would like to know whether the portfolio credit risk will increase if the volume remains the same but the portfolio structure changes, we calculate scale weights.

Applying the formula (4) on Table 4 and Table 5, we can calculate the proportional weights shown in Table 7.

Table 7 Proportional weights

		Applicant's income (US$)			
		< = 0	**1 – 12,000**	**12,001 – 34,650**	**34,651+**
Age	< = 35	0,644398	1,288795371	0,644397685	1,288795371
	36 – 65	0,644398	1,933193056	1,288795371	0,644397685
	66+	0,644398	0,644397685	0,644397685	2,577590742

Source: author's calculation.

Bad rate calculation was made before and after each weighting. Weighting was done using the weight function in SPSS programming package on the presented data set. The results are shown in Table 8.

Table 8 Bad rates before and after portfolio weighting (%)

Bad rate (original portfolio)	**Bad rate (weighted portfolio) – scale weights**	**Change in bad rate– scale weights**	**Bad rate (weighted portfolio) –proportional weights**	**Change in bad rate– proportional weights**
26.4	25.4	-1	25.4	-1

Source: author's calculation.

Table 8 shows that, if we increase the portfolio by targeted segments, the bad rate will decrease by 1%. The portfolio credit risk falls by 1% in case we increase portfolio members by 676 clients with targeted characteristic (scale weights). The portfolio credit risk falls by 1% if we change the portfolio structure by including targeted segments without increasing the portfolio volume.

If we look deeply at the details of univariate analysis, we can see that the segment whose structure/volume (age 36-65 years, and applicant's income range 1-34650.00 $) has been increased is a less risky segment. The weight of evidence measure shows positive values for both segments, and it is expectable that an increase in the structure/volume of that segment of the portfolio would decrease the portfolio credit risk.

When we make business plans we have to take several parameters into consideration, the risk parameter being only one of them. Another important parameter could be profitability, because even if we reduce the credit risk, profitability for the targeted segment could be lower, and at the end we have not made any progress. On the other hand, we could increase the portfolio credit risk, but profitability would also be much higher, which means that potential loss could be covered by higher interest or higher income. The proposed methodology is concentrated on the risk aspect, but that aspect should be combined with other parameters if we want to include all relevant information for business decision-making.

In our example, we only used the application data attributes, available in the data set. The attributes used could also be macroeconomic factors, especially if we base our predictions on behavior scorecards. In that case, we could make scenarios taking into consideration macroeconomic changes and measuring the sensitivity to macroeconomic changes of our portfolio.

3.4 Finding an optimal solution

Portfolio planning can be done using the presented methodology, but there is no prescription for making an optimal segment mix for bad rate minimization. On the other hand, we have to take into consideration profitability factors, strategic frames, long term company policy and other important criteria.

Weight of evidence values for significant factors could be general indicators of which segments should be increased if we want to reduce the portfolio credit risk. In the process of creating several possible scenarios which show significant positive deviations in the portfolio credit risk, the analyst, in cooperation with the management, proposes one of them showing the best performance. A variety of different factors in the simulation can show the real portfolio sensitivity. In the previous example (for the sake of simplicity) we used only two most significant factors for the analysis. The fact is that sometimes a relatively weak attribute in combination with other relatively weak or strong attributes can give us unpredictable results.

The previously presented methodology based on a scoring model and weights could be applicable if we observe just a few variables. If we want to measure the sensitivity of the portfolio credit risk based on a larger number of variables we need much more complex methods like Bayesian networks.

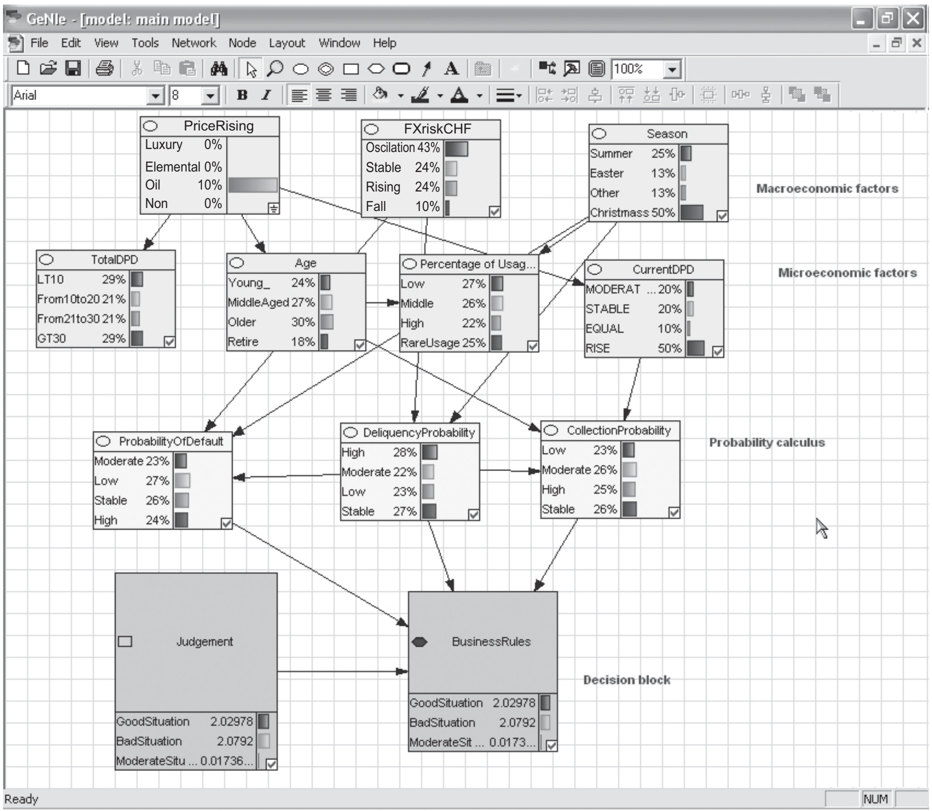
3.5 The use of Bayesian networks

As an illustration of how to use Bayesian networks for analyzing portfolio sensitivity to credit risk caused by structural, volume and macroeconomic changes, the Bayesian network model was created in the GeNIe software package.

As previously mentioned, we use Bayesian networks when we want to involve a larger number of attributes in measuring portfolio sensitivity to credit risk. A Bayesian network also gives us an opportunity for a synergic effect regarding integrated business logic as influence links.

Figure 2 shows a hypothetical Bayesian network created in the GeNIe software package for analyzing the portfolio sensitivity to credit risk which is based on both microeconomic and macroeconomic variables. The data sample was randomly generated regarding the created Bayesian network model.

Figure 2 A Bayesian network for analyzing portfolio credit risk



Source: screenshot from the GeNIe; modeled by author.

The created model could learn from data. As an example, the developed model could be used for the evaluation of rising/falling delinquency probability, default probability, and collection success if oil price are rising, the season is summer, Fx risk on CHF is high, targeted clients are middle-aged …

The Bayesian network is a very good choice for a complex simulation of sensitivity to credit risk, which consolidates numerous microeconomic and macroeconomic variables.

4 Conclusion

The proposed methodology can be helpful in future portfolio risk planning (the use of weighting techniques and scorecards). Depending on the chosen strategy, the applied methodology gives an opportunity to simulate the consequences of potential business decisions. Regarding this, it is possible to evaluate the potential future portfolio risk which is directly caused by the planned future portfolio structure, or potential changes in the market (altered macroeconomic conditions).

Instead of an educated guess, the proposed model offers reduced uncertainty in business decision making

A methodology based on weighting operates with only a few most significant variables, which is sufficient for that kind of simulation and planning. The weighting methodology can be applied for including microeconomic and macroeconomic variables into the model. The planning process can be completed with a profitability parameters calculation, while including market parameters as a basis for making high-quality business decisions. Depending on the strategy and the given calculation, it is possible to find an optimal solution for either a risky but more profitable portfolio which can cover potential planned losses, or a less risky, but less profitable portfolio, if we prefer a conservative approach.

When including more than just a few parameters in the model, Bayesian networks should be used. Bayesian networks can operate with numerous variables.

From the perspective of practical experience, a methodology based on weighting techniques can be sufficient for qualitative analysis, because this methodology focuses on the factors which contribute most to portfolio risk sensitivity.

The model can also be used for campaign planning and portfolio sensitivity analyses, and can be extended on potential crisis analyses. The quality of the model could be improved by including LGD and EAD estimates to generate a profit and loss distribution. .

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