ESTIMATION OF CUSTOMER DEFAULT BASED ON BEHAVIOURAL VARIABLES

Nóra Felföldi-Szűcs
Department Finance
Kecskemét College, Corvinus University of Budapest
Izsáki street 10, Kecskemét 6000, Hungary
E-mail:szucs.nora@gamf.kefo.hu

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ABSTRACT

The paper focuses on the estimation of customer default amoung the small and medium enterprises (SME). Based on the literature on credit scoring modelswebuild a logistic regression model which is widely used by commercial banks. Our models predicting customers' default on their payables to suppliers are estimated on a sample of a customer portfolio of 905 SME clients. Based on the analysis the non-financial, behavioural variables estimate better customer default than the financial ratios. Our models perform weaker than the usual performance level of scoring models in commercial bank. This result assumes that defaulting on a payable to suppliers is an early signal of possible financial difficulties.

INTRODUCTION

As the actors in all kind of credit contracts even firms offering trade credit to their customers are exposed to credit risk. This idea is built into their practice when making decisions on offering delayed paying called trade credit to the group of reliable customers but requiring prompt payment from less opac partners. The decision made by the firms is based on all the important information considered by commercial banks when offering credit to their borrowers. Hago (Hago 2001) describes in his paper the corporate credit policy and as part of it the corporate credit analysis.

Based on the less formal practice of a huge part of firms we will formalize our analsys and a we will apply the credit risk modeling methodology of banks to the customer portfolio of a firm trading in construction materials. We compare the classification accuracy of financial and behavioural variables in the case of SME customers. The findings harmonize with the practice of the claim management firm who provided me the database. The paper describes the applied methodology and tha database. After forming the hypothesis we estimate the models forecasting customers's nonpayment. After the results we finally conclude.

THE APPLIED METHODOLOGY AND THE DATASET

The literature of credit and default risk modeling is rather abundant, and what is more, these keywords often lead to writings with surprisingly differing contents. From a historical approach, it is the accounting-based, so-called credit risk scoring models we will first encounter in literature. Accounting-based models are based on financial ratios derived from the financial / accounting statements of the companies; according to the values taken by these ratios, businesses are divided into two groups: bankrupt and solvent firms. More on accounting based models can be found in the works of a number of international and Hungarian authors, like (Altman and Saunders 1997, Liao et al. 2005, Platt and Platt 1990 or Kiss 2003, Virág 2004 and Oravecz 2008. Relevant pieces of literature clearly distinguish between loans for SMEs and those for large corporations, thus the related risk assessment methodologies are reasonably expected to be different, too. Authors focusing directly on SME borrowers mention the logistic regression as the most widespread model (Atiya 2001 és Laitinen and Laitinen 2000) and most of the authors uses logistic regression for their own estimates of firms' default (Altman and Sabato 2007, Falkenstein et al. 2000) . We will follow their practice in this research.

The trade credit database consists of the customer portfolio of a real-life company. This business is a member of a multinational group of corporations with several subsidiaries in Hungary, trading in construction materials. The total open receivables are of 2.6 billion HUF (ca. 8 million EUR), the delayed receivables of 1.4 billion HUF equal the sales revenue for 46 days. Besides the open receivables totals from all the 905 SME customers of the company, a record of overdue amounts and an aged balance of accounts receivable was also provided. These being stock variables, the figures relate to one specific day. In addition to the agreed credit limit, information (partly of a qualitative nature) on the customer, its manager and its payment history also appear in the database; these will be included in the quantitative analysis as dummy variables. Thus the variables that are given or can be defined for each and every customer are as follows: Aged balanced of open and overdue receivables; detailed breakdown of open and overdue receivables by due date as of the date

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examined; the amount (if any) purchased/paid back between the two dates can be established; how many times the customer appeared on the so-called blacklist (record of non-paying customers) of the claims management company; whether the owner/manager has held a similar position in a company that went bankrupt or had to be liquidated; whether there is anything suspicious about the company (tax (and similar) arrears, foreclosure initiated against the company, frequent changes in place of residence and scope of activities, the credit line extended by the supplier, if any, the amount (if any) by which the credit line was exceeded) can be established.

Non-payment was defined through a dummy variable (DEF90) which equals 1 if the customer is more than 90 days past due, 0 otherwise. An important remark to the above is that these definitions do not coincide with the criteria of bankruptcy and even less so with those of the company's liquidation – they intend to describe a less extreme situation when non-payment „only" affects the supplier. Variable DEF90 is primarily based on the New Basel Capital Accord (Basel II), which defines a defaulted borrower as anyone who is more than 90 days behind with their payments (BIS 2006). Even though our own definition of DEF90 and that of Basel II takes the exact same form, an important distinction is to be made depending on whom the client is indebted to. We made the assumption that it is companies' suppliers who first suffer from late payments, and it is only afterwards, if further financial difficulties arise, that they dare fall behind with or default on their obligations to banks. Accordingly, our nonpayment variables describe a situation 'weaker' than either bankruptcy or a default on a bank loan, which must be taken into account when constructing our model and when interpreting the findings. But variable DEF90 defines a delay of payment far more larger than the average days of delay of the portfolio thus one can assume that it captures the difference on a delay and of a default. This weighted average delay of the customers are 55 days.

As a final step in data collection,wealso looked up the company's key balance sheet and income statement figures in order to aid our later analyses. The financial rations used during modeling are as follows:

- Total Liabilities/(Total Liabilities + Owner's Equity)
- Earnings Before Taxes/Net Sales Revenue
- Earnings Before Taxes/Total Assets
- EBIT/Total Assets
- EBITDA/Net Sales Revenue
- EBIT/Net Sales Revenue
- Net Earnings/Owner's Equity (ROE)
- Current Assets/Current Liabilities
- Total Liabilities/(EBIT + Income from Financial Transactions)
- Total Liabilities/EBITDA
- EBIT/Expenses on Financial Transactions
- Current Liabilities/Net Sales Revenue
- Current Assets/Total Assets
- Total Receivables/Total Liabilities
- Owner's Equity/Fixed Assets
- Net Sales Revenue/Total Assets
- Net Sales Revenue/Net Working Capital
- Net Sales Revenue/EBIT
- (Earnings Before Taxes+Expenses on Financial Transactions)/Total Assets
- Profit on Ordinary Activities/Owner's Equity
- Net Working Capital/Total Assets
- Cash and Cash Equivalents/Current Liabilities
- Long-Term Debt/Owner's Equity
- Total Receivables /Owner's Equity
- Long-Term Debt/ /(Total Liabilities + Owner's Equity)
- Total Receivables/(Total Liabilities + Owner's Equity)
- Net Sales Revenue/Net Working Capital
- Cash and Cash Equivalents/Total Assets
- Current Liabilities/Owner's Equity
- Cash and Cash Equivalents/Net Sales Revenue
- (Net Sales Revenue t=1/Ne Sales Revenue t=0) -1
- FCFF/Total Assets

As many others had used it in bankruptcy modeling, we also used logistic regression to predict non-payment; from amongst the simpler methods, this is the most widely used one and it is considered rather successful, as well (Falkenstein 2000; Grunert et al 2005). Relying on relevant literature (Altman and Sabato 2007; Falkenstein 2000; in Hungary Kristóf 2008a-b) each model variation employed the Forward Stepwise Likelihood Ratio algorithm with significance levels of 5 percent and 10 percent for entry and removal, respectively. The sample was partitioned into a training and a holdout sample according to the 75% - 25% ratio recommended by literature (e.g. Imre 2008).

The studies we read all determined the cutoff value in very different ways. The cutoff value of the model is a threshold for the estimated probability of default: if the latter is lower /higher than the cutoff value then the model predicts the client in question to pay on time /to default on the payment, respectively. Oravecz (2008) and Tang-Chi (2005) discuss the determination of cutoff values for default prediction models in detail. Oravecz (2008) distinguishes between theoretical and empirical determination. The theoretical method relies on profit matrices. Money should be lent to the client as long as the expected profit of lending is higher than the expected profit of refusal. Oravecz (2008) even provides a numerical example and according to her empirical results, the cutoff should rather be determined using the theoretical method if and when profit maximization is the goal. Empirical approaches examine the model's effectiveness for different cutoff values. Yet each author has their own interpretation of effectiveness. Oravecz (2008) sticks with profit maximization, while Tang-Chi (2005) offer a number of different solutions. They cite Altman (1968) having chosen cutoffs based on classification accuracy. Frydman, Altman and Kao (1985), for example, minimized the number of misclassifications, while Ohlson (1980) opted for the intersection of the probability distributions of good and bad debtors.

Current literature primarily features cutoffs given by the largest AUC (area under the curve), arrived at by comparing AUC values calculated using a number of different cutoff values and choosing the one generating the maximum AUC. This is also the method we are going to use in our paper.

THE HYPOTHESIS

Our hypothesis is that the classification accuracy of the models relying solely on non-financial variables is not worse than that of the models using financial data only. Even though the range of non-financial information available to me is rather limited, we still intend to compare the discriminative power of financial statement data with that of other, non-financial data based on Altman, Sabato and Wilson (2010) and Lehman (2003). One of the motives for formulating this hypothesis was that the claims management company that provided me with the database had made recommendations to its client – the supplier – on the line of credit to be extended to each customer primarily based on non-financial indicators, that is, on a kind of expert system.

MODELS PREDICTING DEFAULT ON CUSTOMER RECEIVABLES

The model variation named „MULTIVAR_FIN_015" uses nothing else but publicly available financial data (financial ratios and publicly available blacklists of financially distressed firms, but no behavioural indicators), thus it can be used for new customers, too. The number "015" indicates that the optimal (AUC-maximizing) cutoff value is 15 percent. Accordingly, clients are classified as good debtors if their estimated probability of default is below 15 percent, and "bad" (i.e. non-paying) customers otherwise. For this very model, the results are presented in detail. For the second modell only a shorter overview will be available.

Table 1: Parameters of model MULTIVAR_FIN_015
Source: SPSS

Name of variables	B	S.E.	Wald	Df	Sig.	Exp(B)
number of blacklist appearences	.245	.087	8.023	1	.005	1.278
abilities/Total Debts	2.436	.404	36.274	1	.000	11.429
Owners' Equity/Fixed Assets	.005	.002	3.732	1	.053	1.005
Net Sales evenue/Total Assets	-26	.086	6.882	1	.009	.798
Cash and Cash uivalents/Total Assets	1.786	.674	7.026	1	.008	5.964
FCFF/Total Assets	.775	.209	13.734	1	.000	2.171
Constant	-183	.347	84.241	1	.000	.041

According to the SPSS-output, the significant explanatory variables of customer default in the case of new customers are: the number of blacklist mentions, Total Liabilities/Total Debt, Net Sales Revenue/Total Assets, Cash and Cash Equivalents/Total Assets, and FCFF/Total Assets. The fact, for example, that Customer 'A' has been mentioned on a blacklist one single time results in their odds becoming 1.278 times the odds of an arbitrary Customer 'B' whose significant variables are identical to those of Customer 'A' except that Customer 'B' has never been added to any blacklist.

Table 2: Goodness-of-fit indices for model MULTIVAR_FIN_015
Source: SPSS

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerk R Square
1	511,963	0,058	0,099
2	498,222	0,079	0,134
3	490,464	0,09	0,154
4	483,7	0,1	0,17
5	476,435	0,11	0,188
6	470,034	0,119	0,204

From amongst the goodness-of-fit indices, Nagelkerke R^2 is the easiest to interpret, because it works like the coefficient of multiple determination, taking values between 0 and 1 (Oravecz 2008). Consequently, the explanatory power of our model relying solely on publicly available financial information, is 20.4 percent.

As a next step we estimated a model based on behavioural variables (MULTIVAR_BEHAV_015). Even though the studies discussed in the methodological chapter used a rather wide range of data, our database was limited to the following variables: legal form of the company, repayment, number and duration of blacklist appearences, track record of the company and related persons, and the existence and the exceeding of a credit line. Therefore this model, similar to Altman's ZETAmodel, also includes the ln(Total Assets) indicator as a proxy variable of company size. Similarly, negative Owner's Equity balances were also taken into account through a dummy variable. Final results are listed in Table 3. The indicators found to be significant were: track record of the company (comphist_dummy), payment habits, exceeding of the credit line and negative owner's equity.

Table 3: Parameters of model MULTIVAR_BEHAV_015
Source: SPSS

Name of variables	B	S.E.	Wald	Df	Sig.	Exp(B)
number of blacklist appearences	0,264	0,102	6,664	1	0,01	1,303
number of blacklist days	0,004	0,002	3,725	1	0,05	1,004
firmhistory_dummy	-0,614	0,271	5,156	1	0,02	0,541
repayment_dummy			6,552	2	0,04	
repayment_dummy(1)	-0,4	0,268	2,22	1	0,14	0,67
repayment_dummy2	-0,968	0,384	6,354	1	0,01	0,38
excedding creditline_dummy	-1,528	0,247	38,305	1	0	0,217
negative equity_dummy	1,562	0,414	14,233	1	0	4,767
Constant	-0,258	0,307	0,707	1	0,4	0,772

Table 4: Goodness-of-fit indices for model MULTIVAR_BEHAV_015
Source: SPSS

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	502,803	0,072	0,123
2	486,494	0,096	0,164
3	473,59	0,114	0,196
4	468,116	0,122	0,209
5	460,938	0,132	0,226
6	457,414	0,137	0,234

RESULTS

Based on the literature on relevant methodologies, we examined the hypothesis concerning the logit models classifying customers either as payers or non-payers. The comparison of our models also serves the purpose of evaluating the hypothesis. The aspects of comparison are listed in Tables 3 and 4 showing three goodness-of–fit indices. The estimation algorithm minimizes the value of -2Loglikelihood, thus: the lower the better. Concerning Cox-Snell R^2 values, however, it is the higher values that are more favorable. This indicator, by the way, compares the likelihood value to the empty model (Oravecz, 2008, Sajtos and Mitev, 2007). The interpretation of Nagelkerke R^2 has already been discussed earlier.

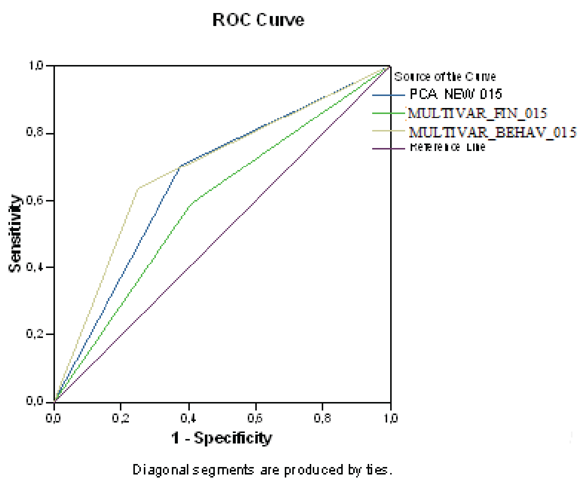
Model MULTIVAR_BEHAV_015, only employing behavioural and non-financial indicators as explanatory variables, was estimated for the purpose of testing this hypothesis. The goodness-of–fit indices and the AUC values of both the training sample and the holdout sample (see Tables 5 and 6) all support that replacing financial ratios with variables describing other dimensions of companies' behavior yielded a better-performing model. Based on the presented models, hypothesis has been accepted, that is, the classification accuracy of the models relying solely on behavioural variables is not worse than that of the models using financial data only. As an interesting note: the acceptance of hypothesis also explains the practice of the claims management company providing our database – namely, that they can successfully determine the credit lines to be extended to customers based primarily on behavioural variables and only secondarily on financial data.

Table 5: Testing of hypothesis – goodness-of-fit indices
Source: SPSS

Entire sample	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
MULTIVAR_FIN_015	470,034	0,119	0,204
MULTIVAR_BEHAV_015	457,414	0,137	0,234

Table 6: Testing of hypothesis – AUC
Source: SPSS

Training sample	AUC	Std. Error	Asymptotic Sig.	Asymptotic 95% Confidence Interval	
				Lower Bound	Upper Bound
MULTIVAR_FIN_015	0,686	0,029	0,000	0,628	0,743
MULTIVAR_BEHAV_015	0,703	0,029	0,000	0,646	0,760
Test sample					
MULTIVAR_FIN_015	0,591	0,048	0,063	0,497	0,686
MULTIVAR_BEHAV_015	0,693	0,047	0,000	0,602	0,785



Figures 1: ROC curves for the holdout sample
Source: SPSS

CONCLUSIONS

The success of the MULTIVAR_BEHAV_015 model suggests that the receivables managing company could improve its decision making mechanism by collecting more behavioural information. The literature recommends for instance the age of the customer relationship, the age of the buying company, the number of the employees, the education of the leaders of the firm, the leader's experience measured in years in the industry, the variability of the balance of the received trade credit, the industry and its industrial bankruptcy rate.

There is also a further research question related, namely to examine the classification power of other nonfinancial indicators. The goodness of fit and the classification power of the models are slightly weaker than the similar values of the bankruptcy and scoring models. A possible reason is that suppliers are generally paid late. A delay on supplier payables does not mean such a severe event of credit risk with serious consequences like bankruptcy or a delay towards a bank. Imre (2008), who developed models for the prediction of bank loan defaults (delays beyond 90 days, in accordance with the default-definition of Basel II), drew the same conclusion at the end of his dissertation. Thus, most probably, the financial data of bankrupt businesses can be better distinguished from that of non-bankrupt businesses than the data of payers can be from that of non-payers. Adopting the reasoning of Imre (2008), a delay beyond 90 days on one's bank loan payment is a "weaker" event than bankruptcy, yet it is an even less severe credit risk situation if it is „only" the supplier who has to wait more than 90 days for their money. So late payment to suppliers is such an early signal for possible financial difficulties that the financial data of the firm can not reflect yet. Consequently, we regard the goodness-of-fit indices and the AUC values of our models as appropriate in spite of the fact that literature frequently reports of better performing models.

All of this however brings up another research question: could the models be improved if we reformulated the definition of customer non-payment which was the dependent variable in the logit models? This non-payment definition would be probably customized to the industry which the customer belongs to. It has to be an early signal about illiquidity and insolvency to assure that the supplier has still enough time to make suitable steps for the collection of the receivables. On the other hand the delay classified as non-payment should be sufficiently long to differ from the common, average delays of 50-60 days in the examined portfolio, so it can be modeled as a dependant variable and can be predicted in advance.

There would be additional research possibilities for the future if chronological data would be available for the aged balance of open receivables. First the circle of the behavioural variables could be broadened by a detailed knowledge on historical paying and purchasing habits. Second, the stability of the paying patterns could be tested. There is an interesting question, whether a customer from the current database classified as a delayer between 31-60 days was in the same due date interval in an earlier point of time, or he/she had belonged to the group of 16-30 days delayers earlier. This last finding would mean that the client is permanently falling behind towards the longer delays. It is also possible, that until a particular due date interval the classification is stabile, afterwards the customer stops his/her payments and his/her classification is going to be worse by the time. If the latter supposition is true, then the observation of this threshold in the due date structure can help to construct a non-payment definition. If the historical value of open balances is available, then there is an opportunity to control and to test the results and the prediction power of the logistic models which are classifying the paying and the non-paying customers.

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AUTHOR BIOGRAPHY

NÓRA FELFÖLDI-SZŰCS was born in Zalaegerszeg, Hungary and went to the Corvinus University of Budapest, where she studied financial investment analysis and risk management and obtained her degree in 2006. After a short experience at Deutsche Bank she began her PhD studies at Corvinus University where she has been lecturer since 2006. She obtained her PhD degree in 2013. Since 2015 she has been the coordinator of Business Administration Program at Kecskemét College. Her e-mail address is : nora.szucs@uni-corvinus.hu.