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ASSESSMENTS OF CREDITWORTHINESS OF CRAFTS IN CROATIA

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ABSTRACT

The main purpose of the paper is to analyse financial reporting practice in the craft sector and to assess the quality of the financial and qualitative data available. For this purpose, the credit scoring as methodology was used. Here, evaluation of the information produces model which is enabling the crafts' creditworthiness assessment. In terms of empirical research, the importance of qualitative data is confirmed. Due to the fact that crafts in majority are oriented towards local markets, the model has potential to be applied on local level management in financial institutions and within the crafts' suppliers. Overall, this promotes better inclusion of the crafts within their business environment.

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I. INTRODUCTION

According to the Craft Act (OG 2007/68), a Craft is an independent and continuous performance of allowed economic activities, performed by a person in a non-industrial way. At the end of 2012, the Croatian Chamber of Trades and Crafts reports 83,714 active crafts, with a total of 188,871 employees (HOK, 2013: 7-17). This data highlights the importance of crafts for the national economy. The performance data in the crafts sector needs to be presented in order to show clearly the scope and elements of their business activities, whilst respecting the requirement for a sufficient amount of data for a quality financial analysis.

Despite the above mentioned arguments, and the clear importance of the Crafts sector in the national economy, these enterprises are neglected by the accounting profession. The focus remains mainly on the other types of the business entities. The accounting and financial reporting of companies is regulated in detail by the Accounting Act, International Accounting Standards and the Croatian and International Financial Reporting Standards. On the other hand, accounting and financial reporting of the crafts is regulated by the Income Tax Act (OG 177/2004) only.

Various types of decision-makers, i.e. business entities engaged in business activities with crafts, require additional accounting data. In addition, their clients frequently require documents from various institutions (mostly tax administration and banks). These documents are not always available, due to the time constraints faced by entrepreneurs. Thus, financing craft activities generates an increase in the lender's cost of risk, an increase of the debtor's costs of obtaining and securing a loan, as well as cause a significant extension of the approval period. Since crafts are representing a significant part of the Croatian economy, understanding their financial reporting and reliable assessment of their creditworthiness represents a foundation for successful business relationship with those entities.

The main objective of the paper is to empirically research the real power of information from the crafts' financial statements. Moreover, the focus in the paper is to evaluate the effect of the inclusion of selected additional data. In this way, additional financial and non-finacial data will be recognised, enabling a quality assesssment of the crafts' creditworthiness as well as the quality of doing business with these enterprises. Finally, an additional objective is to compare the models for assessing crafts' creditworthiness at the beginning of the financial crisis (2008-2010) and the models which account for the five years of the financial crisis (2008-2013).

The paper will be structured as follows: following the introduction, the objective of the section two is to describe the conceptual framework of the analysis. At this point, the interdependence between financial reporting within the craft sector will be established by using various types of variables and the scoring models used by banks. In section three, dataset description and methodology will be presented followed by the empirical results of the model. In addition, some concluding remarks are presented in the last section.

II. THE CONCEPTUAL FRAMEWORK IN THE ANALYSIS

The small size of enterprise implies the market orientation. In case of crafts, the local market[1] is the dominant type. Moreover, the importance of industry where craft entities participate is lower in comparison to other business entities. The competitive advantage is based on the entrepreneurs'

[1] This term includes a market of several neighbourhood counties.

knowledge and related to low level of technology within the craft. This is closely linked with the non-industrial way of conducting a business activity. Therefore, the success of crafts' business venture depends on the entrepreneurs' characteristics, experience in terms of the particular business activity as well as other characteristics such as the number of generation involved in the current business activity. Their small size implies that financial reporting of these companies is not organised to a satisfactory degree. This could explain that on average loans to crafts[2] are smaller in comparison to other types of business entities.

Despite the fact that number of the crafts have been diminished during the period 2003-2012 (17.6 percent points), large number of active crafts in population of all types of legal entities[3] imply their importance in terms of local and national markets in Croatia.

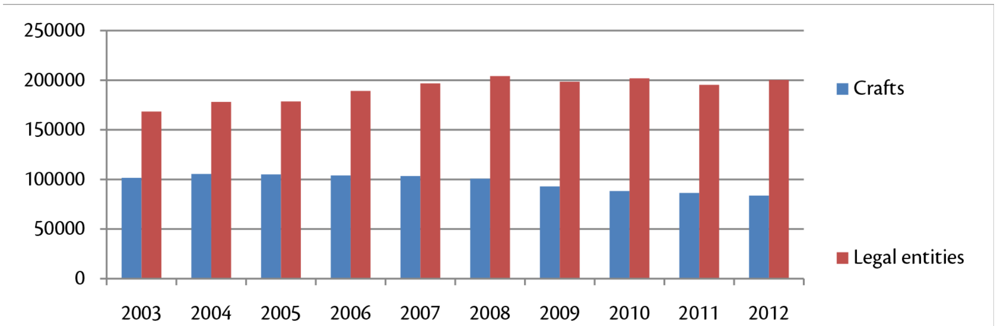

FIGURE 1 – THE NUMBER OF ACTIVE CRAFTS AND LEGAL ENTITIES IN CROATIA (2003-2012)

Source: Authors' calculation based on the available reports (HOK, 2013: 7; HOK, 2012: 6; HOK, 2011: 7; HOK, 2010: 7; HOK, 2009: 6; HOK 2008: 13)

The analysis of the business risk presents the focal point of the craft's business analysis where various stakeholders from the financial sector as well as their clients show interest. The business risk in terms of crafts performance presents the probability of the particular craft sucessfully fulfilling their business obligations. The differences in terms of business risk exist between the various types of companies, where the main objective of the risk analysis within the business entities is to model firm credit events of financial distress that are assumed to occur unexpectedly (Liang, 2003: 14). Therefore, the fulfillment of the crafts' obligations depends on entrepreuners' characteristics related to their business activities, personal information[4], level of crafts' debtness, as well as on the amount of credit received from the financial institutions. In large extent, these groups of variables describe the crafts' business practice where credit institutions, tax administration and clients are the main groups of institutions interested in this practice. Differences within business risk between various types of business entities imply existence of various types of models regarding creditworthiness assessment, which are research models, statistical models, clausal models and hybrid models (Thonabaure, Nosslinger, 2004). In the absence of relevant theoretical

[2] This is similar to Peek and Rosengren (1998: 27-37) statement that scoring model shows the best result in terms of small amount of the loan up to 100 000 USD.

[3] The Company Law (OG 111/1993) defines foundation, and setting of legal entities in Croatia, as well as it defines following types of the legal entities limited liability company, corporations, limited partnership, craft, and subsidiary of foreign legal entities and/or individuals. So, the banks use the same approach regarding classification of their clients.

[4] For example gender, age, marital status, educational level, occupation

agreement concerning the choice of variable (Abdou, Pointon, 2011: 11) one may assume that the choice of the group of the variables within the craft sector is a result of past experience about the crafts' business activities and/or the result of experience of the similar business entities, e.g. SMEs, where similar group of variables appear such as information about personal data (e.g. Šušteršič et al. 2009, Hand et al. 2005), information about the business entities' activities, and information about financial loans (e.g. Ong et al. 2005, Lee, Chen, 2005). Therefore, systematic approach which includes various groups of qualitative and quantitative variables have to describe the aforementioned factors influencing the fulfilment of the crafts' obligations. There is very little in terms of the business risk estimation within the craft sector in terms of impact on transaction costs as well as potential increases in business expenditure. Thus, stakeholders interested in a particular craft's business activity have a specific interest for adequate business risk estimation. In case of the implementation there are several areas where improvement of crafts' perfomence could be expected: 1) Interaction between the craft owners and their environments[5]; 2) Decrease in the loan prices 3) Incresase of credit availability (cf. Feldman, 1997).

Acceptance of systemic logic in the analysis of the crafts' performance requires an appropriate tool for managerial decision making, i.e. credit scoring. This is a statistically derived tool which is aiming to provide appropriate information for managament about their clients, based on quantitative and qualitative data. In general, there are two main ways of use of such data in practice. Firstly, managment within the financial institution could receive information about the significant variables within the analysed groups, whereas secondly the each business entity receive its score. Thus, in former case the model is a combination of model results and subjective knowledge of management responsible for the decision making where in latter case the result of the model are the only reliable inputs for decision making. The aforementioned quantitative and qualitative data within their group receive numerical values and the sum of the numerical values presents the business entities' score. However, the presence of high levels of informal cooperation (e.g. exchange of information) among the enterprises with small number of employees and their clients in environment is closely linked to the existence of asymmetric information within business environment where crafts are participants. This could influence a suboptimal choice of variable group. Therefore, the main purpose of the scoring model is to give an appropriate bulk of information to financial management about their clients. Here, the acceptance rate is based on approvals of application volume; adherence to expected core distribution; frequency of reversing score decision; bad rate loan losses versus profitability could be results of using the score method and at the same time useful for the financial management engaged in score modeling (Leonard, 1993: 80).

The financial crisis (from 2008 onwards) emphasizes the financing problem within the craft sector. Taking into consideration that crafts are, on average, smaller than small and medium enterprises, they are more vulnerable to credit rationing as a type of risk mitigation or elimination technique which consists of aborting or reducing lending, and is not a result of avoiding selection of an excessive risk from an individual credit or specific portfolio (Kundid, Ercegovac, and 2011: 2). As a result, the existence of pressure on craft's financial ability to meet its obligations may increase parallely with decrease of the local markets (this is main reason of GDP decline in the last five years in Croatia), and as a consequence can affect the entrepreneurs within the craft sector to leave and/or change the market and their professional occupation.

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[5] As result of the increase reliability and accountability of the crafts' performance.

III. DATASET AND ECONOMETRIC MODELLING

As highlighted previously, this paper explores the reliability of business decisions based on financial statements of crafts as well as other financial and non-financial (qualitative) data on crafts. This data is required to produce models with a suitable level of reliability, enabling the assessment of creditworthiness of these entrepreneurs. The data for this analysis has been obtained by one Croatian bank[6].

In this paper two samples of data are used primarily in order to observe the differences within the craft sector - specifically, at the onset of the financial crisis (2008-2010) and over the five years of the ongoing financial crisis (2008-2013)[7]. The former sample contains data for 684 crafts in Croatia, where transport and trade (17.4%) represents the most important sector in the data, followed by the construction sector (15.9%) and hotels and restaurants (9.5%). The latter sample contains data for 1424 crafts in Croatia in the period 2008-2013. The main sector in this sample is transport (15.3%), followed by the trade (14%) and construction sector (9.6%). Comparing the former sample in the latter sample there are significant number of unclassified crafts (18.3%), the crafts which did not declare their main activity or they have more than one activity of equal importance. In addition, the proportion of the craft within the construction sector has declined by 6.3 percentage points during two observed periods.

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[6] According to the authors' best knowledge, the sample within the paper includes around 25%-30% of all financed crafts in Croatia.

[7] We create two samples in order to achieve information about the crafts' performance during the financial crisis from 2008 to onwards.

TABLE 1 – SAMPLE STRUCTURE BY INDUSTRIES

	Sample 1		*Sample 2*	
	Number of crafts	***%***	***Number of crafts***	***%***
Unclassified	0	0.0%	261	18.3%
Transport, storage and communication	119	17.4%	218	15.3%
Wholesale and retail trade	119	17.4%	199	14.0%
Construction	109	15.9%	137	9.6%
Real estate and renting	53	7.8%	123	8.6%
Hotels and restaurants	65	9.5%	120	8.4%
Agriculture, hunting, forestry and fishing	30	4.4%	62	4.3%
Other community, social and personal service activities	16	2.3%	61	4.3%
Health and social care	23	3.4%	58	4.1%
Manufacture of metals and metal products	29	4.2%	37	2.6%
Manufacture of paper, publishing and printing	23	3.4%	25	1.8%
Food and drink industry	8	1.2%	23	1.6%
Other manufacturing and recycling	15	2.2%	20	1.4%
Production of textiles and clothing	19	2.8%	19	1.3%
Production of rubber and plastic products	13	1.9%	18	1.3%
Wood processing	14	2.1%	13	0.9%
Production of electrical and optical equipment	13	1.9%	12	0.8%
Production of chemicals and chemical products	0	0.0%	4	0.3%
Production of transport equipment	0	0.0%	4	0.3%
Manufacture of machinery and equipment	4	0.6%	3	0.2%
Financial intermediation (excluding banks and saving banks)	0	0.0%	2	0.1%
Manufacture of leather and leather products	2	0.3%	2	0.1%
Public administration and defense	2	0.3%	1	0.1%
Education	2	0.3%	1	0.1%
Manufacture of other non-metalic mineral productrs	6	0.9%	1	0.1%
Total	684	100%	1424	100%

Source: Research Results

There are differences between Sample 1 and Sample 2 in terms of the regional distribution of the financed crafts. In Sample 1, during the period 2008-2010, Zagrebačka County was a leading county in number of the financed crafts (26.2%), followed by Istarska County (14.6%) and the Zagreb City (13.7%)[8]. In Sample 2, during the period 2008-2013, the largest population of the financed crafts was from Zagrebačka county (32.9%) followed by, the Zagreb city (15.8%) and Varaždin county (13.5%)[9] (For more details please see Appendix)[10].

Furthermore, the credit scoring as a methodological approach for assessing the crafts' creditworthiness was used and is defined as the likelihood that a prospective borrower will default on a loan (Abdou, Pointon 2011: 3). The first phase of the credit scoring application applies use of the logistic regression aiming to generate the optimal number of independent variables.

The basic formula of logistic regression:

$$P\left\{Y = \frac{1}{X}\right\} = \frac{1}{1+e^{-x\beta}} \tag{1}$$

$$X\beta = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots \beta_K X_K$$

The value of the logistic function is limited between 0 and 1. A value of 0 is obtained in the case of x = - ∞, the value of 1 for x = ∞, and for x = 0 function value is 0.5. In comparison to other similar model (e.g. linear regression) its main advantage is that the outcome variable in logistic regression is dichotomous (a 0/1 outcome). This will enable the alternative classes of the credit, namely "good" credit and "bad" credit. So, the logistic functions help to choose the optimal number of the independent variables which describe the depended variable from various sources.

A bi categorial variable with two values was used as a depended variable, i.e. orderly settlement of the debt by craft and no pay back of debt by the craft. The positive business performance is described by the former value, whereas the other group of the crafts which do not meet their obligations is described by the latter value. The latter group of the crafts require meeting the preselected criteria over the period of the last six months, which are recorded block of their bank accounts, arrears of more than thirty days and a tax debt of more than five percent of total annual income.

As performance evaluation technique within the credit scoring model the ROC (Receiver Operating Characteristic) curve is used[11]. It is graphical presentation represents the proportion of *bad debtor* classified as bad cases versus the proportion of *good debtor* classified as good cases. Usually, ROC is curve connecting points (0.0) and (1.1). The model which is not able to distinguish (discriminate) good from bad debtors, a *random model*, has a ROC curve in the form of longitude connecting points (0.0) and (1.1), while the *ideal model* which perfectly depict both bad and good debtors has ROC curve in the form of longitude connecting points (0.1) and (1.1) (Figure 1).

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[8] In the same period, the largest average number of the active crafts was in the Zagreb City 16243, followed by Splitsko-Dalmatinska County 10767.3 and Primorsko-Goranska county 9323.7 (HOK, 2011: 7, HOK, 2010: 7, HOK, 2009: 6).

[9] Unfortunately, we have no available information about the number of active crafts for the same period.

[10] Since the crafts from the Zagreb City are on the third place in terms of the financed crafts (Appendix- Table A1, Sample 1), and the largest population of the active crafts is located in the Zagreb City,we may assume that the empirical models (fourth part of the paper) will better explain crafts' economic activities, within the counties in the continental part of Croatia in comparison with the counties on the Adriatic Sea.

[11] Where the logistic function explains optimal number of independent variables, the ROC curve answers the questions which are the most predictable variables that explain depended variable.

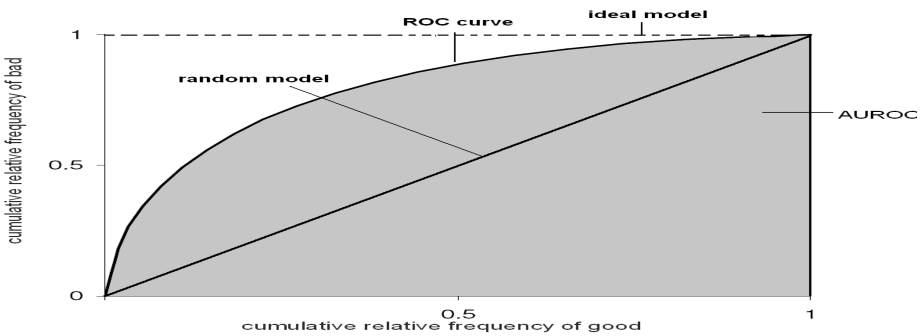

FIGURE 2: RECEIVER OPERATING CHARACTERISTIC CURVE

Source: Authors' calculation

The area under the ROC curve is a measure of quality of the model (Tape, 2004)[12]:

0.5 - 0.6 - fail model

0.6 - 0.7 - weak model

0.7 - 0.8 - fair model

0.8 - 0.9 - good model

0.9 - 1.0 - excellent model[13]

Information value refers to the ability of the model to distinguish the two distributions: debtors meeting their obligations on time and debtors who do not. Higher information value implies that model differentiates better between good debtors and bad debtors. The formula for calculating the value of information is as follows:

$$IV = \sum_i IV_i = \sum_i (B\%_i - G\%_i) * ln\left(\frac{B\%_i}{G\%_i}\right) \tag{2}$$

where:

IV_i Informational value of certain category

$B\%_i = \frac{B_i}{\sum_j B_j}$ where B_i is frequency of “good” in each category

$G\%_i = \frac{G_i}{\sum_j G_j}$ where G_i is frequency of “bad” in each category

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[12] Despite of the fact, that reference Tape (2004) isan internal presentation of the University of Nebraska, according to google scholar citation index, it was cited three times.

[13] The reliability ofthe empirical models (Table 3, Table 4, Table 5 and Table 6) are assessed in their second part named Association of Predicted Probabilities and Observed Responses.

The minimum value of the information value of the statistics is 0, and as such the sufficient level of predictability between good and bad borrowers is not predictive. Variables, depending on the value of information value of statistics, can be ranked as follows (Siddiqi, 2006):

< 0.02 - variable is not predictive

0.02 - 0.1 - variable is poorly predictive

0.1 - 0.3 - variable is moderately predictive

> 0.3 - very predictive variable

All variables with the information value of less than 0.1 were discarded from further consideration.

In terms of the indepedent variables, the following groups of the variables are included in the group: *Based on financial data from tax returns* (a), *Based on the tax returns and other financial data from other sources* (b) and *Based on qualitative data about the craft* (c).

TABLE 2: GROUPS OF INDEPEDENT VARIABLES

1. Variables based on financial data from tax returns	
a1	gross income / receipts
a2	(gross income + amortization) / receipts
a3	gross income
a4	gross income > 33.8 thousands kuna (minimal monthly average brutto wage on year average)
a5	book value of fixed assets / gross income
2. Variables based on all available financial dana	
b1	current assets / current liabilities
b2	money / current liabilities
b3	annual payables for long-term loans and leasing / (gross income + amortization)
b4	working capital / total assets
b5	gross income / total assets
3. variables based on qualitive data about the craft	
c1	number of years in business
c2	economic activity
c3	age of the owner of craft
c4	number of generations in the family involved in the business
c5	education of business owner
c6	number of employees
c7	business experience in the current industr

Source: Research Results

IV. EMPIRICAL RESULTS OF THE MODEL

Four models were created in order to estimate the probability that the craftsmen will meet their financial obligations in orderly fashion. The first model uses only variables extracted from financial data available from tax returns for the period 2008-2010. Similarly, the second model uses variables formed on the basis of financial data from tax returns and other available financial data for the same period. The third model expands on the set of financial variables (the second model) with qualitative variables for the period 2008-2010, whereas the fourth model analyses crafts during the period 2008-2013 and includes the same group of variables used in the third model. Since the variables are based on time series, variables for current year are additionally labeled with "cur" and those based on previous year are additionally labeled with "pre". Indicator "C" from the last table in all four models is a measure of the quality of the whole model. Higher value of this indicator means that model has greater predictive power.

The most predictive variables in model I (Table 3, first part) are *variables gross income/receipts* (a1), *gross income > 33.8 thousand kuna (minimal monthly average brutto wage on year average)* (a4) in current and previous time, *(gross income + amortization)/receipts* (a2) in current and previous time, and variable *book value of fixes assets/gross income* (a5). Moreover, the variable a4 in previous time is statistically significant within the model and it is explaining the probability that the craftsmen will manage to meet their obligation.

TABLE 3: MODEL I -VARIABLES BASED ON FINANCIAL STATEMENTS, SAMPLE I

Analysis of Maximum Likelihood Estimates

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq	Standardized Estimate
Intercept	1	-2.6939	0.4325	38.797	<.0001	
a4_CUR	1	-0.2468	0.1387	3.1667	0.0752	-0.1924
a4_PRE	1	0.3519	0.1208	8.4885	0.0036	0.2923
a1_CUR	1	0.1387	0.2433	0.325	0.5686	0.1081
a1_PRE	1	-0.0335	0.2719	0.0152	0.902	-0.0288
a2_CUR	1	0.0405	0.2416	0.0281	0.867	0.0316
a2_PRE	1	-0.1089	0.2773	0.1543	0.6945	-0.0936
a5	1	0.0537	0.0981	0.299	0.5845	0.0418

Association of Predicted Probabilities and Observed Responses

Percent Concordant	59.6	Somers' D	0.206
Percent Discordant	39	Gamma	0.209
Percent Tied	1.4	Tau-a	0.041
Pairs	46739	C	0.603

Source: Research Results

The model based on these variables is successful in 60.3% of cases (C=0.603) (Table 3, second part). This data implies that this model will recognize that crafts are not able to meet their financial obligations in only 60.3% of cases. Thus, this model has a relatively weak predictive capability.

The model I (Table 3) enables a separate calculation for each craft, based on the probability that financial obligations will not be met, using the following formula:

$$\text{PD} = 1/1 + e\,\hat{}\,\hat{}(-2.6939 + \text{a1\_CUR}^*0.1387 + \text{a1\_PRE}^* - 0.0335 + \text{a2\_CUR}^*0.0405 + \text{a2\_PRE}^* - 0.1089 + \text{a4\_CUR}^* - 0.2468 + \text{a4\_PRE}^*0.3519 + \text{a5}^*0.0537 \quad (3)$$

where PD is the probability of default.

Adding the available financial data in the model II (Table 4) enhances the number of reliable variables and the predictability of a craft not being able to meet its financial obligations. The most predictive variables are *current assets/current liabilities* (b1), *money/current liabilities* (b2), *annual payables for long-term loans and leasing / (gross income + amortization)* (b3), *working capital/total assets* (b4), *gross income/receipts* (a1), *gross income > 33.8 thousands kuna (minimal monthly average brutto wage on year average)* (a4), *(gross income + amortization)/receipts* (a2) in current and previous time, and variable *book value of fixes assets/gross income* (a5). Moreover, the variables b3 and a4 in previous time are statistically significant variables and similar to previous model, and are explaining the probability that the craftsmen will orderly meet their obligation.

TABLE 5: MODEL II BASED ON ALL AVAILABLE FINANCIAL DATA, SAMPLE I

Analysis of Maximum Likelihood Estimates

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq	Standardized Estimate
Intercept	1	-2.8788	0.5548	26.9265	<.0001	
b1	1	-0.1486	0.0953	2.4295	0.1191	-0.1158
b2	1	-0.0608	0.0839	0.526	0.4683	-0.0553
b3	1	0.1826	0.0698	6.8331	0.0089	0.1734
b4	1	0.1778	0.1562	1.2959	0.255	0.0816
a1_CUR	1	0.1983	0.2428	0.6671	0.4141	0.1546
a1_PRE	1	0.041	0.2876	0.0203	0.8866	0.0353
a2_CUR	1	-0.0475	0.2393	0.0394	0.8427	-0.037
a2_PRE	1	-0.1938	0.2931	0.4372	0.5085	-0.1665
a4_CUR	1	-0.2634	0.1427	3.4075	0.0649	-0.2054
a4_PRE	1	0.3685	0.1235	8.9015	0.0028	0.3061
a5	1	0.0741	0.0997	0.5523	0.4574	0.0578

continued table

Association of Predicted Probabilities and Observed Responses			
Percent Concordant	65.4	Somers' D	0.318
Percent Discordant	33.6	Gamma	0.321
Percent Tied	1	Tau-a	0.064
Pairs	46739	C	0.659

Source: Research Results

Based on these variables, model II is successful in 65.9% of cases (C=0.659) (Table 4, second part). Therefore, regardless of more predictive power comparing model II, this model is still grouped as a weak model (between 0.6-0.7).

Similar to the previous model, the model II enables a separate probability calculation of a default using the following formula:

$$PD = 1/1 + e\hat{}(-2.8788 + b1^* - 0.1486 + b2^* - 0.0608 + b3^*0.1826 + b4^*0.1778 + a1\_CUR^*0.1983 + a1\_PRE0.041 + a2\_CUR^* - 0.0475 + a2\_PRE^* - 0{,}1938 + a4\_CUR^* - 0.2634 + a4\_PRE^*0.3685 + a5^*0.0741; \quad (4)$$

where PD is the probability of default.

In the scenario of adding financial and qualitative data the following variables are predictive: money/current liabilities (b2), annual payables for long-term loans and leasing/(gross income + amortization) (b3), age of owner of craft (c3) and number of employee (c6) are reliable in terms of prediction that the craft will not meet its financial obligations orderly. Within the model variable b3, c3 and c6 are statistically significant and explain the probability of a default.

TABLE 5: MODEL III - VARIABLES BASED ON FINANCIAL AND QUALITATIVE DATA, SAMPLE I

Analysis of Maximum Likelihood Estimates						
Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq	Standardized Estimate
Intercept	1	-2.5736	0.4901	27.5731	<.0001	
b3	1	0.2088	0.068	9.4263	0.0021	0.1983
b2	1	-0.0829	0.0815	1.0355	0.3089	-0.0753
c3	1	-0.2225	0.0914	5.9248	0.0149	-0.1726
c6	1	0.2505	0.0825	9.2134	0.0024	0.2072
a4_PRE	1	0.173	0.0918	3.55	0.0595	0.1437
a4_CUR	1	-0.1535	0.0964	2.5343	0.1114	-0.1197

continued table

Association of Predicted Probabilities and Observed Responses			
Percent Concordant	69.1	Somers' D	0.394
Percent Discordant	29.8	Gamma	0.398
Percent Tied	0.9	Tau-a	0.079
Pairs	46739	C	0.697

Source: Research Results

Based on these variables, model III (Table 5) is successful in 69.7% of cases (C=0.697) what is still marginally below the threshold for fair successful models. However, this implies that reasonable predictability can be achieved using models that include, both financial and qualitative variables, in order to increase the power of the predictability.

Similar to the previous models the probability of credit default of particular craft can be calculated for each craft separately by the following formula:

$$PD = 1/\left(1 + e\hat{\ } - \begin{pmatrix} -2.5736 + b3{*}0.2088 + b2{*} - 0.0829 + c3{*} - 0.2225 + c6{*}0.2505 + \\ a4\_PRE{*}0.1730 + a4\_CUR{*} - 0.1535 \end{pmatrix}\right) \quad (5)$$

where PD is the probability of default.

Finally, in order to explore possible changes in the behavior of crafts during the financial crisis over the past five years, the fourth model has been established (Table 6). This model used variables based on all financial and qualitative data, (similar to the model III), but using data from sample 2 (see Table 1). Consequently, statistically significant variables within the model were *annual payables for long-term loans and leasing/(gross income + amortization)* which are most able to explain the probability of a default.

TABLE 6: MODEL IV - VARIABLES BASED ON FINANCIAL AND QUALITATIVE DATA, SAMPLE II

Analysis of Maximum Likelihood Estimates						
Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq	Standardized Estimate
Intercept	1	-2.4001	0.3229	552.377	<.0001	
b3	1	0.1285	0.047	74.745	0.0063	0.1182
b2	1	-0.0522	0.0498	11.012	0.294	-0.0499
c3	1	0.0482	0.0593	0.6599	0.4166	0.0377
c6	1	0.0466	0.0562	0.6869	0.4072	0.0407
a4_PRE	1	0.0172	0.067	0.066	0.7972	0.0135
a4_CUR	1	-0.0387	0.0629	0.3786	0.5384	-0.0303

continued table

Association of Predicted Probabilities and Observed Responses			
Percent Concordant	55.8	Somers' D	0.14
Percent Discordant	41.7	Gamma	0.144
Percent Tied	2.5	Tau-a	0.029
Pairs	206640	C	0.57

Source: Research Results

Resulting from model IV and in comparison to the previous calculations in the other three models, the probability of a default is calculated by the following formula:

$$PD = 1/(1+e^{-}(-2.4001 + b3*0.1285 + b2*-0.0522 + c3*0.0482 + c6*0.0466 + a4_P RE*0.0172 + a4_C UR*-0.0387) \quad (6)$$

where PD is the probability of default.

Predictive variables in the model IV are identical to the model III. However, model IV has a significantly lower predictive power in comparison the model III (Table 6, second part). Despite the significantly larger sample size and longer time series, this model is only slightly better than random models. These results can be explained with significant behavioral changes in crafts in conditions of financial crisis. An indicator of increased risk of doing business within the craft sector during the financial crisis is a significant share of craftsmen in Sample 2 which did not declare their main activity or have two or more activities of equal importance.

V. CONCLUDING REMARKS

The research recognizes the importance of qualitative data in the creditworthiness assessment of the craft sector. The recognition of appropriate variables has an impact on the management in financial institutions as well as on local level suppliers as it provides the basis necessary for appropriate decision making in the case of the business with crafts.

Using a scoring model as a technique reveals the value of using this data in assessing a craft's creditworthines. In addition, it facilitates more efficient external financing of crafts. Regarding the empirical models, it is found that the creditworthiness assessment using the score model is closely related to similar business entities in terms of number of employees (e.g. SME). Consequently, it seems that using data from financial statements as well as the qualitative data enables the extraction of the variables necessary to perform a useful analysis of the crafts' business activities in Croatia.

Moreover, an additional result of this research is that crafts' creditworthiness based on the quantitative variables does not generate reasonably acceptable results. The reliability of the model is only 66% (based on the sample for the period 2008-2010). It is only for with the inclusion of qualitative data that the reliability of the model for assessing the creditworthiness of crafts increases to an suitable level (70%). These values were based on the sample for the period 2008-2010. Additional and useful variables to estimate the default probability are annual payables for long-term loans and leasing/(gross income + amortization), the number of employees and age of the owner.

Following the calculation on a larger sample over a longer period (2008-2013), the results indicate a decrease in the reliability of the model (from 70% to 57%). Intuitively, this could be explained by the fact that craft's activities during the financial crisis are significantly different in comparison to what may be termed as normal circumstances, i.e. before the period 2008 onwards, and by the fact that number of unclassified crafts in 2013. significantly increased in this paper sample (18.3%). As a result, a new set of the variables are required in order to explain the craft's behaviour in the new circumstances, i.e. the financial crisis.

To conclude, this research yields an interesting finding which can contribute to the understanding of the creditworthiness assessment, and can enhance the potential for the use of the credit score models in the craft sector in Croatia. Due to the fact that the model recognises reliability of the information about the crafts' business activities via appropriate variables, the use of credit score models has the potential to be extended and indeed benefit local level management in financial institutions, as well as the suppliers. At the same time, the application of the credit score model faciltates financing of the crafts, and is decreasing craft's transaction costs as well as an increasing their business efficiency.

An interesting topic for further research would be to increase the empirical basis of the model by including behavioural variables, e.g. the number of days of delay in meeting commitments. Moreover, the application of the agent theory within the craft sector and new model scoring techiques, such as neural network and decision three model, could be applied. In addition, the topic for further research, which can be interest to analyse, is the assessment of the impacts of the financing crisis and its influence on the craft sector, as well as the assessment of cogntive variables which can explain how people think and act in organisations.

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APPENDIX

TABLE A1 – PROPORTIONS OF THE FINANCED CRAFTS IN COUNTIES

	Sample 1	*Sample 2*
BJELOVARSKO-BILOGORSKA COUNTY	1.46%	0.24%
BRODSKO-POSAVSKA COUNTY	3.51%	2.92%
THE ZAGREB CITY	13.74%	15.76%
ISTARSKA COUNTY	14.62%	9.61%
KARLOVAČKA COUNTY	0.58%	3.15%
KOPRIVNIČKO-KRIŽEVAČKA COUNTY	4.24%	1.81%
KRAPINSKO-ZAGORSKA COUNTY	7.89%	6.07%
MEĐIMURSKA COUNTY	0.00%	1.81%
OSJEČKO - BARANJSKA COUNTY	3.36%	2.76%
POŽEŠKO-SLAVONSKA COUNTY	0.00%	0.71%
PRIMORSKO-GORANSKA COUNTY	4.24%	3.70%
SISAČKO-MOSLAVAČKA COUNTY	1.02%	1.65%
SPLITSKO-DALMATINSKA COUNTY	0.88%	0.39%
VARAŽDINSKA COUNTY	12.72%	13.48%
VIROVITIČKO-PODRAVSKA COUNTY	3.95%	0.32%
VUKOVARSKO-SRIJEMSKA COUNTY	0.73%	2.60%
ZADARSKA COUNTY	0.88%	0.08%
ZAGREBAČKA COUNTY	26.17%	32.94%

Source: Research results