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INSOLVENCY RISK PREDICTION USING THE LOGIT AND LOGISTIC MODELS: SOME EVIDENCES FROM ROMANIA

Abstract. *The authors have studied insolvency situation from Romania in the aftermath of the 2008 financial crisis, using 5 years of financial statements data for 70 Romanian companies from different economic sectors, which all entered insolvency in 2013. We have designed a model for predicting insolvency risk which can be used by any interested party, since the data for the model are readily available on the site of Romanian Fiscal Administration Agency. The model uses five financial ratios, whose dynamics is analyzed for at least three years. To test the model we have used a logit and logistic model, which validated the significant influence of total assets efficiency and accounts receivable conversion period upon insolvency risk. As such, managers and investors can follow especially the evolution of these two measures a*nd make the best credit and investing decisions concerning analyzed companies.

Keywords: *Romanian insolvencies; prediction model; economic and financial measures; logit and logistic models.*

JEL Classification: L10, M10

Introduction

In Romania recent years have accounted for a large number of companies which became insolvent, turning the issue of estimating this risk into a priority, both for managers (which need tools to predict and control the potential risks faced by their companies), as well as for trading partners (who need such information to design proper commercial credit and investment policies in relation with the analyzed company).

Most insolvency risk studies were based on multivariate, discriminant analysis, whose results were used to generate score functions to estimate companies' state of health. However, many insolvency risks' predicting models present a range of shortcomings which makes them not applicable to all the companies requiring insolvency risks' forecast at a certain moment in time. On the one hand, many of these models were aimed for companies listed on the stock exchange and on the other hand, even if such models are not intended for listed companies, they are based on accounting information not accessible to external users, thereby significantly reducing the range of models' potential users. In the same time, score functions' based models have, due to their invariable coefficients, an applicability confined to the economic-geographic area for which they were created. As such, the coefficients determined by authors according to the economic-geographic features of the industry and country for which they were designed, require caution while using them, even in case of similar geographic and economic conditions, yet at different moments in time.

Unlike managers, which have at their disposal detailed information about their companies' economic and financial situation, the trading partners of unlisted Romanian companies cannot access other information than excerpts from these companies'financial statements data, published by the National Agency for Fiscal Administration (NAFA) on its website. Moreover, this information is processed and summarized and thus insufficient to be used in established prediction models to determine insolvency risk.

We propose a model for insolvency risk's diagnosis which can be used by any party (especially external users) interested in the health of a Romanian company, based on public and official information originating from its annual financial statements, whether listed or not on the Stock Exchange and regardless of its size. The model is primarily intended for trading partners, who can thus establish the economic and financial health of their potential partners and identify those facing insolvency risk. Based on this information they can further decide about the opportunity of initiating or continuing their business relations.

The reminder of the paper is organized as follows: section two approaches literature review; section three presents Romania 2013's insolvency situation; section four approaches the model to estimate insolvency risk and data analysis; section five is dedicated to model testing, whilst conclusions are presented in section six.

1. Literature review

Starting with the 2008 global economic crisis, insolvency became a concept subject to numerous studies and debates. Many researchers from Romania and abroad analyzed and debated the delicate/thorny issue of economic entities' insolvency.

European cross-border insolvency rules are established by EC's Regulation 1346/2000 (Insolvency Regulation) regarding insolvency proceedings, applicable starting May the 31-th 2002.

In Romania insolvency is regulated and defined by art. 3, paragraph 1, of Law 85/2006 as "the state of the debtor's heritage characterized by lack of funds available for payment of due debts". From a legal perspective, the causes leading to the dissolution of a company are those provided by Law 31/1990 on trading companies, republished, and are divided into common causes for all types of companies and specific causes for equity companies, respectively for partnerships.

There are a variety of models for predicting bankruptcy. In the literature we can find several types of insolvency risk prediction models, respectively MDA (Multiple Discriminate Analysis) models, logical regression models, neural networks' models or mixed logit ones.The scoring method has become very popular over time due to its use of statistical methods for financial situation's analysis, starting from a set of ratios. The most common scoring method's models are Altman's, Springate's, Koh's model, Conan-Holder's, and the one of Banque de France.Scientific models for bankruptcy prediction based on financial indicators have been developed for the first time in the USA in the 1960's, by Altman (1968) and Beaver (1966). The first wide range model of bankruptcy risk analysis, commonly known as the Z score function, belonged to Altman, who published it firstly in 1968. Altman's model is based on the discriminate analysis, creating classification/prediction models which include data and observation in certain *a priori* determined classes. Altman et al. (1977) built another model known as *Zeta* model, analyzing 53 bankrupt and 58 viable companies during 1969-1975.

Ohlson (1980) and Platt & Platt (1990) conducted the first studies using the logit model for predicting companies' state of insolvency. Zmijewski (1984) advanced the probit model to predict companies' bankruptcy risk. The econometric models are based on logit and probit models in particular. Default-prediction literature acknowledged logit model as being the most used technique to determine default's probability. The results of Ohlson's model have shown that firm size, financial structure, performance and current liquidity were the main determinants of companies' insolvency. Shumway (2001) proposed a hazard model for predicting bankruptcy firms, defined as a multi-period logit model. One main feature of the hazard model is that explanatory variables vary over several time periods, resulting in more efficient estimators. In his work he studied 300 bankrupt firms from the 1962 to 1992 period. Decision trees method for predicting insolvencies (the advantages of using CHAID classification trees compared to a neural network model) was used by Zheng and Yanhui (2007).

Bankruptcy is due to economic and financial factors, negligence, fraud, as well as other factors. Economic factors, causing 37.1% of bankruptcies, relate particularly to industry weakness and unfavorable location. Financial factors, holding the highest percentage, of 47.3%, include too much debt and insufficient capital. The analysis showed that most financial factors relate to huge errors, misjudgments, and management's reduced capacity of financial prediction (Brigham and Ehrhardt, 2007).

There are many causes of business failure, some related to managers' experience and skills, while other causes are due to general economic conditions, the recession. As such, Burksaitiene and Mazintiene (2011) aim to provide managers with information about possible causes and consequences of failure in their companies. Other authors tried to demonstrate Altman's model effectiveness in predicting retail companies' financial difficulties (Hayes et al., 2010). Kiyak and Labanauskaitė (2012) conducted a comparative analysis for several models of bankruptcy prediction and reliability, concluding that linear discrimination model most accurately reflected the financial position of the company (for companies in Lithuania). Pereira and Machado-Santos studied the way the established predictive models can be applied in various fields or types of economies in different countries, analyzing Portugal's textile companies insolvency (2007); Zeytinoglu and Akar (2013) attempted to identify bankruptcy risk for Istanbul Stock Exchange listed companies; Gharaibeh et al. (2013) analyzed insolvency of Jordan Stock Exchange listed companies (the applicability of prediction models for emerging economies - the case of Jordan); Szeverin and László (2014) analyzed bankruptcy prediction models' efficiency for small and medium size entities in Hungary. Recent studies (Karas and Režňáková, 2014) examined how bankruptcy prediction model's efficiency is influenced by the choice of a certain method, especially the linear discriminant analysis method.

In Romania studies developing scoring functions for bankruptcy's risk analysis occurred much later compared to research conducted worldwide. Anghel (2000) conducted a comprehensive bankruptcy risk study, creating a score function based on a sample of 276 companies. Generally, the idea of limiting the findings and applicability of a score function only to the economic sector for which it was built is widely accepted, even if it turned out that some models have a high degree of applicability. This is because the models recognized worldwide were built under a stable economy, while the Romanian economy is still under a long process of consolidation.

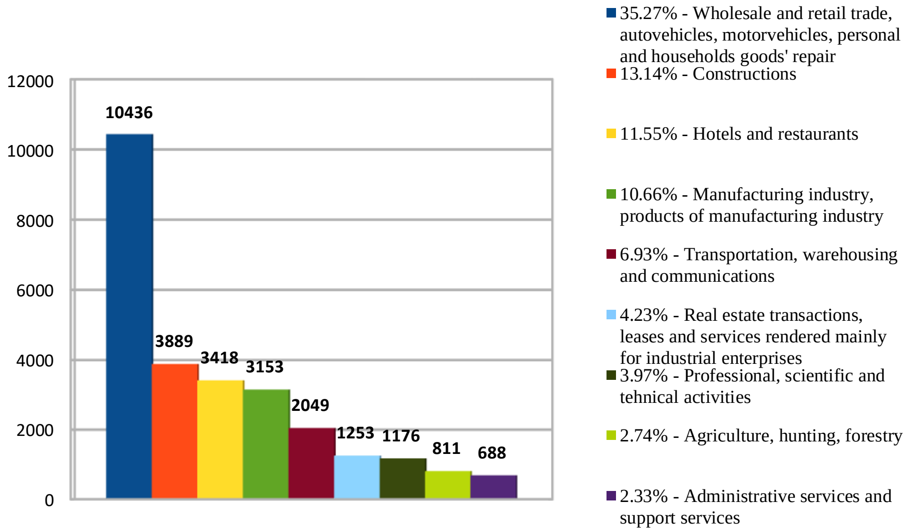
Studies concerning bankruptcy risk's estimation, aimed to discriminate bankrupt companies from the ones with a good financial situation, based on financial ratios, have been conducted by Vintilă and Toroapă (2012), which developed a bankruptcy predicting econometric model. Korol and Korodi (2011) aimed to demonstrate Fuzzy logic's effectiveness in predicting bankruptcy risk and proposed an econometric model in this regard.To highlight the financial strength and ability to meet obligations of Romanian companies listed on Bucharest Stock Exchange, Armeanu et al. (2012) have performed an Altman scoring function on a sample of 60 companies, using seven financial indicators, representative for company's activity: total assets, net turnover, operating result, net cash flow from operating activities, net profit, debt – total liabilities and average market capitalization.

2. 2013 Romania's Insolvencies Situation

The situation of Romanian companies which entered into a state of insolvency in 2013 has been studied so far mainly from the points of view of its evolution, of insolvencies distribution's fluctuation from a geographical point of view or according to field of activity, many studies in this area belonging to Coface Romania. According to information published by Romania's National Trade Register Office (NTRO) after a slight improvement (a decrease of 9.41%) in 2011 compared to 2010, in 2012 followed a strong growth of 36.42% in the number of recorded insolvencies. The increase of insolvencies' number continued in the year 2013, exceeding by 10.37% the ones recorded in 2012.

Most insolvencies were recorded in Bucharest city, representing 12.70% of 2013's total number of insolvencies in Romania. Bucharest was followed by Bihor, Galati, Brasov and Constanta counties, which recorded between 4.08% and 6.17% of all insolvencies recorded in Romania in 2013. These four counties, together with Bucharest accounted for a third of all 2013 Romanian insolvencies, with remaining Romanian counties recording a less significant number of insolvencies, holding each between 0.73% and 3.80% of total amount. The territorial distribution showed no areas with a high concentration of insolvencies.In figure 1 we present Romania's 2013 sectorial distribution of insolvencies.We can notice that most companies which entered into insolvency state activated in the fields of wholesale and retail trade, motor vehicles service, motorcycles and personal and household goods, representing more than one third of all insolvencies recorded in Romania in 2013.

Figure 1. Main sectors affected by insolvency in Romania, 2013



Source: NTRO, data processed by authors

3. The Model to Estimate Insolvency Risk and Data Analysis

The purpose of our paper is to develop an insolvency risk's diagnosis model, usable by any party interested in an economic entity's health. The model can be applied by users with access to detailed financial statements, as well as by people with access only to summary information published by financial authorities. Unlike models based on score functions, influenced by invariable coefficients, our model is based solely on financial ratios fluctuations' analysis over time. In this way, the model can be applied to any company, regardless of the economic, geographical and temporal conditions. This study was conducted under the conditions of eliminating any outside influences, specific for the industry, geographic area, size of companies or the general health of the economy, relying exclusively on economic and financial information derived from the annual financial statements published by the commercial companies.

The model, designed for an early warning of financial difficulty of economic entities, is based on a set of five measures, respectively *general solvency*, *patrimonial solvency*, *accounts receivable conversion period*, *assets' liquidity* and *assets' efficiency ratio*. The selection of financial indicators was conditioned by the availability of financial data provided by Romania's Administration of Public Finance.

To identify insolvency symptoms' occurrence, we have analyzed 350 financial statements from the last 5 years prior to insolvency of 70 Romanian economic entities. For all the 70 economic entities the insolvency proceedings opened in 2013. Our model is designed to identify the elements which help assess the probability a company enters a state of insolvency, respectively the elements signaling decreasing financial stability of analyzed economic entities.

Sampled economic entities, described in Table 1, originated from 12 activity sectors, and were completely randomly selected, without any focus on certain sectors of activity, territorial settlements and size of economic entities. The purpose was to generate a basis for heterogeneous research, able to provide generally valid and reliable results.

Table 1. The activity sector of the sampled economic entities

Sector of activity	**No. of analyzed entities**
Wholesale and retail trade, repair of motor vehicles, personal and household goods	16
Constructions	13
Manufacturing, Manufacturing products	13
Hotels and restaurants	8
Transport, storage and communication	6
Professional, scientific and technical activities	5
Agriculture, hunting, forestry	2

Activities of administrative services and activities of support services	2
Other activities of collective, social and personal services	2
Information and communication	1
Education	1
Water supply; sanitation, waste management	1
TOTAL	**70**

Source: Authors' decision

Analyzing sampled economic entities' financial statements, a first relevant financial indicator regarding insolvency risk and potentially bankruptcy (analyzed in its evolution for 5 years preceding the year of entering into insolvency) is *general solvency*. This measure is intended to provide an overview of economic entity's ability to meet its payments to creditors, both on short and long term, as a a ratio of total assets into total debt and liabilities. In table 2 below we present general solvency's evolution for sampled economic entities over the 5 years preceding their 2013 entering into insolvency.

Table 2. Distribution of sampled economic entities according to their general solvency

General solvency level		**Years of analysis**				
		2008	2009	2010	2011	2012
Unsatisfactory	< 1	28.57%	45.71%	50.00%	50.00%	61.43%
Satisfactory	[1 ; 1.3]	38.57%	32.86%	27.14%	25.71%	22.86%
Good	> 1.3	32.86%	21.43%	22.86%	24.29%	15.71%

Source: Data processed by the authors

The financial statements data revealed that starting with the third year of analysis preceding insolvency, more than 75% of companies showed a decreased general solvency and more than half experienced a reduced capacity of covering their financial commitments to creditors, both on short and long term. In the year preceding official insolvency's state (2012), weight of companies with decreasing general solvency reached over 84%, of which over 61% are already in general insolvency.

Data analysis reveals sampled economic entities are actually insolvent starting with at least three years before the year of entering insolvency and also that their general solvency is decreasing throughout the review period, with a sharp decline in 2012.

General solvency decrease, especially in the year preceding entry into insolvency was due to a slight total assets' decrease during the period 2008-2011 and an abrupt decline in 2012, and to a relatively steady growth of total debt throughout the period under review, also with a sharp increase in 2012.

The second financial indicator we found useful in assessing imminent insolvency risk is *patrimonial solvency*, calculated as a ratio of company's equity into its equity and liabilities (equity + debt + accrued income + provisions). In the five years preceding entry into insolvency state, analyzed companies experienced a continue de-capitalization, with a strong manifestation in 2012. Situation is described in table 3 below.

Table 3. Distribution of economic entities according to patrimonial solvency

Patrimonial solvency level		**Year of analysis**				
		2008	**2009**	**2010**	**2011**	**2012**
Unsatisfactory	< 0,3	72.86%	82.86%	81.43%	80.00%	85.71%
Satisfactory	[0.3 ; 0.5]	10.00%	4.29%	4.29%	10.00%	5.71%
Good	> 0.5	17.14%	12.86%	14.29%	10.00%	8.57%

Source: Data processed by the authors

Financial statements' analysis reveals that, starting with the third year of analysis preceding the entry into insolvency, more than 85% of analyzed companies have registered a low patrimonial solvency, out of which over 80% recorded a significant de-capitalization trend. In 2012, the weight of companies showing decreasing patrimonial solvency reached over 91%, of which over 85% are actual insolvent.

Overall analysis of sampled companies' patrimonial solvency reveals most of them are actually insolvent starting with at least three years before the year of entry into insolvency. Their patrimonial solvency decreased throughout the review period, with a sharp turn in 2012, the year preceding entry into insolvency, thereby achieving a high level of indebtedness both on short and long term.

Analyzed commercial entities showed continuous increase of indebtedness' degree. Their indebtedness recorded very high values in 2012, when analyzed companies' de-capitalization reached peak values. Entering insolvency for an economic entity is closely related to a low assets' liquidity level, which in turn can very easily lead to slowing or even shutting down payments to its creditors.

The third measure we have identified is *accounts receivable conversion period*, or accounts receivable to daily sales ratio. The measure is a reflection of commercial credit policy's effectiveness, a vital instrument of validating company efforts and generating the cash needed for settling financial commitments and resuming company business cycle.

The 70 sample companies recorded, from 2010 and until 2012, for 3 consecutive years, significant and steady growth of accounts receivable conversion period.Thus, in the period prior entry into insolvency, analyzed companies recorded increasing delays in cashing the goods sold or services delivered, making it more difficult to repay existing debt and being subsequently compelled to call in additional debt to continue.

The progressive increase of account receivable conversion period was due to a slight yet steady turnover's decline during the five years analyzed and to a sudden rise of accounts receivable in the last two years' prior entry into insolvency, namely 2011 and 2012; these two elements combined generated a sharp increase of accounts receivable conversion period.

Our model's fourth measure is *assets' liquidity*, or the ratio of current assets into total assets, designed to provide information regarding company's operational flexibility and its capacity to serve commercial and financial commitments.

Analyzed companies recorded, starting with the third year before entry into insolvency, increases of asset liquidity, which could be a positive sign of their ability to service debts and therefore to keep away from insolvency risk.

However, looking further into the evolution of current assets' components, we find that asset liquidity's increase was unhealthy. Two components of this assets liquidity's increase, respectively inventories and cash, fluctuated, yet remained somehow stable during the 2008-2011 period. This was followed by inventories and cash decreases in 2012. Thus, their cumulated evolution for the entire period is negative and opposite of growth tendency registered by assets' liquidity. The only current assets' component which recorded a sharp increase, especially in 2012, is accounts receivable, whose 2012 growth has been strong enough to more than compensate cash and inventories' decreases and determine assets liquidity's increase.However, correlating this with the evolution of accounts receivable conversion period, we find out that, although assets' liquidity grew in the period preceding the entry into insolvency, analyzed companies actually had increasing difficulties in covering their debts as they come due.

The fifth measure we have considered is *assets' efficiency***,** the ratio between company turnover and total assets employed to generate respective sales. Overall, the 70 companies analyzed have recorded a slight decrease in total assets' efficiency.

To illustrate we have analyzed the deterministic evolution 2012/2011 (the most relevant years of the five analyzed) of assets' efficiency ratio, taking into account the two level one influence factors (total assets and sales turnover), as well as second level (fixed assets and current assets) and third level factors (inventories, accounts receivable and cash). The findings are quite relevant and they correspond with the downward overall trend of analyzed companies and the entry into insolvency.

The modification 2012/2011 of average (for the 70 companies) total assets' efficiency was of +3.24 lei (960.05 lei in 2012 compared to 956.82 lei in 2011) and is analyzed in table 4 below, with a deterministic factors' contribution measurement.

Table 4. Factors' contributions to total assets' efficiency modification 2012/2011

Measures	Factors' Contributions
1. Contribution of total assets: $$TAE_{11}\left(\frac{1}{Index\ of\ TA\ 12/11}-1\right)$$	+44.6411
1.1 Contribution of fixed assets: $$TAE_{11}\left(\frac{1}{Index\ of\ TA\ 12/11-K\%CA}-1\right)$$	-8.6356
1.2 Contribution of current assets: $$TAE_{11}\left(\frac{1}{Index\ of\ TA\ 12/11}-\frac{1}{Index\ of\ TA\ 12/11-K\%CA}\right)$$	+53.2768
1.2.1 Contribution of inventories: $$TAE_{11}\left(\frac{1}{Index\ of\ TA\ 12/11-K\%A/R-K\%M}-\frac{1}{Index\ of\ TA\ 12/11-K\%CA}\right)$$	+23.1899
1.2.2 Contribution of accounts' receivable: $$TAE_{11}\left(\frac{1}{Index\ of\ TA\ 12/11-K\%M}-\frac{1}{Index\ of\ TA\ 12/11-K\%A/R-K\%M}\right)$$	-36.3151
1.2.3 Contribution of cash and short-term investments: $$TAE_{11}\left(\frac{1}{Index\ of\ TA\ 12/11}-\frac{1}{Index\ of\ TA\ 12/11-K\%M}\right)$$	+66.4021
2. Contribution of sales turnover: $$TAE_{11}\frac{1}{Index\ of\ TA\ 12/11}\left(Index\ of\ sales_{12/11}-1\right)$$	-41.4028

Source: authors' calculation

Where:

TAE – total assets' efficiency, the ratio of sales to total assets;

Index of TA 12/11 – index of total assets 2012/2011;

$Index\ of\ sales_{12/11}$– index of sales 2012/2011;

k% CA – percentage contribution of current assets tototal assets' change 2012/2011;

k% A/R – percentage contribution of accounts receivable to total assets' change 2012/2011;

k% M – percentage contribution of cash&liquid assets to total assets' change 2012/2011.

From table 4 we can find that total assets' efficiency increased in 2012 compared to 2011 (a level higher by 3.23 lei for 1000 lei invested in total assets).

Nevertheless, this is not a favorable evolution, since it was due to total assets' decrease (thereby creating an apparently positive contribution of 44.64 lei) combined with a milder sales turnover's decrease (with a negative contribution of -41.4 lei). We can substantiate this by deepening total assets' contribution analysis. As such, we can find fixed assets had a negative contribution of -8.64 lei, which reveals that sample companies made a reduced level of investments, most likely destined to replace depreciated fixed assets (obviously creating new fixed assets is virtually excluded under such circumstances).

Furthermore, looking into the structure of current assets we can find that their apparently positive contribution (of +53 lei) was actually due to decreases in inventories and cash and increases in accounts receivable. This corresponds to the perfect recipe for insolvency (lower inventories, hence lower prospects of future sales combined with a slower recovery of accounts receivable and reduced cash amounts).

After checking and correcting data for routing checks, descriptive statistics and means by year of selected ratios are presented in table 5 below.

Descriptive statistics shows selected companies have on average 59% current assets and 41% noncurrent assets. On average selected companies have general solvability ratio of 1.32, respectively patrimonial solvability ratio of -1.31. Moreover, on average, companies generated 2.6 RON of sales for each RON invested in total assets and collected their account receivables in 98 days.

Table 5. Descriptive statistics

Variable	Obs.	Mean	Std. Dev.	Min	Max
AL (assets liquidity)	347	0.59	0.31	0.00	1.00
GS (general solvability)	346	1.32	2.15	0.00	27.74
PS (patrimonial solvability)	347	-1.31	11.09	-200.09	1.00
TAE (total assets effic.)	346	2.60	5.94	0.00	87.57
A/R (Accts. Receivable Conv. Period)	321	98.02	129.69	0.00	781.03
Y (dependent variable)	347	0.66	0.47	0.00	1.00

Source: authors' calculation

4. Data and methodology

4.1. Applying the model

We have applied the model for an economic entity (randomly selected) not listed in the Bulletin of Insolvency Proceedings. Practically, entity's insolvency risk simulation was conducted from a trading partner's point of view.

The model implies calculating the five measures and establishing each measure's negative evolutions from one year to another (labeled *YES* if there is a negative trend and *NO* otherwise). The following steps consist in checking the years in which all five measure showed negative evolutions and finally counting the consecutive years in which all five indicators had negative evolutions. In case of our analyzed economic entity, there was no year in which all five measures concurrently recorded negative evolutions, therefore it appears it presents no insolvency risk. In the same way, the test can be performed for any economic entity, provided there is data available from the financial statements for the last five consecutive years. Table 6 shows means of selected ratios by year. Assets liquidity, total assets' efficiency and A/R conversation period have positive trends, whereas general solvability, patrimonial solvability negative.

Table 6. Means by year

Year	AL	GS	PS	TAE	A/R
2008	0.56	1.98	0.04	2.05	93.95
2009	0.54	1.54	-0.41	2.43	62.31
2010	0.59	1.13	-0.51	2.06	106.03
2011	0.63	1.10	-0.75	2.04	106.00
2012	0.64	0.83	-4.97	4.44	124.02
Total	0.59	1.32	-1.31	2.60	98.02

Source: Data processed by the authors

In case of analyzed economic entity, we can notice a good general and patrimonial solvency, exceeding the 1.3, respectively the 0.5 reference thresholds for general, respectively patrimonial solvency, throughout analyzed period. These values demonstrate economic entity's ability to pay its debts, a low degree of indebtedness and consequently a virtually non-existent insolvency risk. These arguments are also supported by the correlated evolutions of the measures presented in table 7.

Table 7. Indicator evolution analysis

Indicator evolution	**Negative evolution period**			
	2010	2011	2012	2013
Decreasing general solvency (< 1.3)	NO	NO	NO	NO
Decreasing patrimonial solvency (<0.5)	NO	NO	NO	NO
Increasing A/R conversion period	YES	YES	YES	NO
Simultaneous increase of AL and A/R conversion period	NO	NO	NO	NO
Declining of total assets' efficiency	YES	YES	YES	YES
Simultaneous negative trend for all measures	NO	NO	NO	NO

Source: Data processed by the authors

Linking economic and financial measures analyzed here to identify the causes that led the 70 sampled Romanian economic entities into insolvency in 2013 we have noticed a negative trend at least three years before the year of starting the insolvency proceedings (see table 8 below).

Table 8. Negative trend for at least three years

Negative trend	2009	2010	2011	2012
Decreasing general solvency (< 1.3)	YES	YES	YES	YES
Decreasing patrimonial solvency (<0.5)	YES	YES	YES	YES
Increasing A/R conversion period		YES	YES	YES
Simultaneous AL and A/R conversion period's increases		YES	YES	YES
Decreasing total assets' efficiency		YES	YES	YES

Source: Data processed by the authors

An economic entity's potential trade partner can perform the analysis of five financial measures using at least four yearly financial statements and assessing their evolution for at least three years. Based on this set of measures' evolution analysis, we can estimate the level of insolvency risk presented by a potential trading partner and the potential hazards which can affect its economic and financial situation.

Should the five financial measures concurrently display a negative evolution, then, according to the number of years of downside trend, it is possible to determine the level of insolvency risk. If there is just one negative evolution (a negative evolution means that in a given year all the five measures have concurrently negative evolutions), then the company has a low risk of becoming insolvent; if two consecutive negative evolutions occur, then the company records an average risk of going insolvent; and if there are three consecutive years of negative evolutions the company has an increased risk of becoming insolvent.

4.2. General form of the logit and logistic model

We rely our estimations on a Logit and Logistic model, considering a class of binary response models with the following form (Måns, 2009):

$$Pr(Y = 1/x) = G(XB)$$

$$Pr(Y = 1/x) = G(B_0 + B_1X_1 + B_2X_2 + \cdots B_kX_k) \quad (1)$$

where G is a function taking on values strictly between 0 and 1: $0 < G(z) < 1$, for all *z*real numbers. The general form of the model (1) is a function of the *x*vector, through the index:

$$xB = B_0 + B_1X_1 + B_2X_2 + \cdots B_kX_k \quad (2)$$

which is simply a scalar. The condition $0 < G(xB) < 1$ensures estimated response probabilities lie strictly between 0 and 1. G usually refers to the ***cumulative density function*** **(dcf),** and non-linear function which is monotonally increasing in the index *z* (i.e.xB), with:

$$Pr(Y = 1/x) \rightarrow 1, \text{ as } xB \rightarrow \infty$$

$$Pr(Y = 1/x) \rightarrow 0 \text{as } xB \rightarrow -\infty$$

The most common non-linear function is the logistic distribution, yielding the logit model, as follows:

$$G(xB) = \frac{exp(xB)}{1+exp(xB)} = \Lambda(xB) \qquad (3)$$

which has values between 0 and 1, for all values of the *xB*scalar term. The equation (3) refers to the***cumulative distribution function (cdf)***for a logistic variable. Since$Pr(Y = 1/x)$ in the equation (1) is categorical, we use the logit of *Y* as the response in our regression equation instead of just *Y*, as follows:

$$Ln\left(\frac{P_i}{1-P_i}\right) = B_0 + B_1X_1 + B_2X_2 + \cdots B_kX_k \qquad (4)$$

The logit function (4) is the natural log of the odds *Y* will equal one of 0 and 1 categories. *P* is defined as the probability of *Y=1*.

4.3. The logit and logistic model

In this part we use a logit and logistic model to have a more rigorous estimate of selected companies' insolvency risk and validate the results of our previous model. Before running regression, we have checked the data for routine controls. For example, assets liquidity, general solvability, assets' efficiency or accounting receivables conversion period cannot be negative.

Since all selected companies have gone bankrupt we offer in this paper a unique methodology to estimate and evaluate insolvency risk. This case is not treated in previous empirical research. Hence, dependent variable is calculated based on general solvability. General solvability is the main indicator reflecting insolvency risk. As such we transform this indicator into two categories to denote the solvency, respectively insolvency risk. Thus, if a company's general solvability index (with current year against previous year's values) is lower than one, it denotes a solvability concern and is quantified with **1**. Otherwise, if the index has a higher than one value (also with current year against previous year's values) the situation is quantified with **zero**, meaning solvability is not a concern. Thus, the dependent variable takes either *1* or *0* values.

The model we use to analyze the probability that a company becomes insolvent reads:

$$L = \frac{P_i}{1 - P_i} = B_0 + B_1LogAL + B_2LogPS + B_3LogTAE + B_4LogA/R \qquad (5)$$

Where:

L denotes the calculated dependent variable of insolvency; for the comparison we have left solvency outside the model as a benchmark category;

LogAL represents log of assets liquidity;

LogPS the log of patrimonial solvability;

LogTAE the log of total assets' efficiency and

LogAR the log of A/R conversion period.

As logging the level of data variables results in negative observations, (since a large proportion of data from all matrixes of respective explanatory variables contain values above 0 and below 1), we have transformed these data, taking the *log* of explanatory variables in levels added by one (Guerin, 2006). Using this transformation, we take care of negative values and we can interpret the coefficients from LOGIT regression as elasticity for the large values of transformed variable. The situation is represented in table 9 below.

Table 9. Regression results

VARIABLES	**LOGIT**	**LOGISTlC** (Antilog-odds ratio)	**Predicted probabilities**
log of assets liquidity	0.640	0.463	.713893
	[0.67]	[0.60]	
log of patrimonial solvability	-0.160	-0.117	.595157
	[-0.57]	[-0.49]	
log of total assets' efficiency	-1.224***	-1.064***	.596553
	[-2.90]	[-3.12]	
log of A/R conversion period	-0.388***	-0.367***	.840716
	[-2.67]	[-2.97]	
Constant	2.838***	2.614***	
	[3.52]	[3.92]	
Observations	258	258	
Number of groups	67		
Wald chi2(4)	11.34		
Prob > chi2	*0.0230*		
Log-likelihood	-162.38999	-164.73442	
R-square		0.213	
Pseudo R2		0.485	

Notes: z-statistics in brackets, ***, ** and * indicate significance of coefficients at 1, 5 and 10 per cent, respectively.

Source: Authors' calculations

For the estimation purpose, we use LOGIT and Logistic regression as robustness check to logit model. Moreover, the LOGIT model produces predictions more consistent with underlying theory[1], justified as LOGIT assumes log of odds ratio is linearly related to dependent variable, meaning that their marginal effect does not have a constant impact upon dependent variable. It also resolves predicted values' problem, because its logistic function has always values between *0* and *1* for all real numbers. After running the logit regression some important variables resulted insignificant for the 1, 5 and 10% levels. The likelihood ratio and Wald test suggest that we reject H0, respectively insignificant slope coefficients

[1]Whilst Linear Probability Model measures the change in probability of the slope coefficient for a unit increase in the dependent variable, with all other variables held constant, in the Logit model the slope coefficient of a variable gives the change in the log of the odds associated with the unit change in that variable, again holding all other variables constant.

are jointly zero. The *p-value* of the Wald test is 0.0230, so the null hypothesis is rejected at the 5% significance level. Interpreting results in terms of log of odds ratio[2], means we have to account for partial slope coefficients in estimated equation measuring change in estimated logit for a unit change in value of the given regressors (holding other things constant).

4.4. Interpretation of results and discussions

Estimated coefficients of *total assets' efficiency* and *A/R conversion period of* -1.064,respectively -0.367, in the logistic model mean that, other things held constant, *assets efficiency*and *A/R conversion period* are 10.64 and 3.67 times less likely to contribute to company insolvency. Thus, the value of -1.224 from table 9 for total assets' efficiency indicates that, holding other variables constant, *total assets' efficiency* would have a log of odds ratio of contributing to company insolvency, which is 1.22 less than that of a having a log of odds ratio contributing to company solvency, other things being equal. The value of -0.388 for *A/R conversion period* indicates that, other things being equal, *A/R conversion period* would have a log of odds ratio of contributing to company insolvency, which is 0.388 less than that of having a log of odds ratio contributing to company solvency, other things held constant. To find predicted value of log odds ratio, predicted probabilities are calculated taking into account mean values of continuous variables. In terms of predicted probabilities[3] the probability of companies becoming insolvent is of 0.56811 (56.8 per cent)[4](Wooldridge, 2015). Contribution of *total asset liquidity* upon predicted insolvency probability is 71.3 per cent. The contribution of *patrimonial solvability*, *total assets' efficiency* and *A/R conversion period*, upon predicted insolvency probability are 59.51 per cent, 59.65 per cent and 84.07 per cent, respectively.

Regression results show *assets liquidity* and *patrimonial solvability* are insignificant factors for insolvency risk. In other words, assets composition (current assets vs. noncurrent assets) has not played a significant role for insolvency risk. Also, *patrimonial solvability* calculated as equity to total assets has not significantly contributed to insolvency risk. This denotes risk originated from debt financing rather than equity financing.

Total assets' efficiency and *A/R conversion period* are confirmed to be significantly related to insolvency risk with a negative contribution on insolvency. Results are in line with theoretical expectations. Hence, as *total assets' efficiency* increases, insolvency risk decreases. This means in turn that as assets generate more sales, insolvency risk becomes lower. Moreover, as companies decrease *A/R conversation period,* insolvency risk increases too. This means that reducing credit

[2]Odds interpretation is obtained by taking the antilog of various slope coefficients.

[3]To find the predicted value of log odds ratio, predicted probabilities are calculated taking into account the mean values of continuous variables.

[4]For our empirical work we will report the considered usual significance levels, as suggested by Wooldridge (2015), at 10% significance level. Where variables achieve a level of significance just outside of this range, it is noted and recorded as a 'borderline' level of significance.

period to customers generated higher risk. Usually, as *A/R collection period* increases, future becomes more unpredictable and insolvency risk increases as well. However, our result in this case is slightly contradictory. The explanation of this result may be the fact that as companies shortened *A/R conversation period,* clients were more likely to switch to competitors, thus sales decreased.

Conclusions

Our sample with the 70 economic entities, is heterogeneous, with companies belonging to different sectors; they have different size and originate from different geographical areas. It is well known that score functions are appropriate for the period or economic situation in which they were created. Compared to this function, our model, comprising a set of five measures, can provide generally valid and reliable results and allows for data generalization and results' implementation under any economic circumstances.

Correlated analysis of economic and financial measures was meant to shape a clearer picture regarding imminent insolvency risk for the 70 economic entities studied. All five measure composing the model recorded a downward trend (in the last three years preceding the entry in a state of insolvency) and values outside ranges deemed as normal for healthy companies (recording levels lower than the minimum accepted values). From third year-on, more than 50% of analyzed companies experienced deterioration of marked indicators. Thus 75%, respectively 85% of analyzed companies showed a negative general, respectively patrimonial solvency, with a high level of debts toward creditors and failure to serve their due payments. Simultaneously, for three consecutive years, there can be noticed a significant and constant increase of *A/R conversion period*.

Increasing delay in cashing receivables, caused mainly by commercial credit policy relaxation and insufficient analysis of potential credit beneficiaries, was the main insolvency reason. The increasing delays in collecting receivables led to delays in paying debt toward creditors and calling additional debt to continue their business.

A second reason which caused many Romanian companies enter insolvency in 2013, was decrease of assets' efficiency, as companies registered a diminishing turnover along a lesser assets' decrease. This latter evolution is most likely a direct consequence of the delay of transforming receivables into cash (of increased balance of accounts receivable).

The inability to honor creditors' obligations (general solvency with low and declining values), accelerated de-capitalization (unsatisfactory and declining level of economic solvency), growing delays in collecting the value of goods and services sold (increasing A/R conversion period), the lack of real liquidity (declining assets' liquidity) and inefficient use of assets (downward trend of assets' efficiency) are the five measures that, together, led to a situation of imminent insolvency, within a three years' period.

Consequently, there can be seen a correlation of the five economic and financial measures and they have fairly equal influence in their ability to forecast whether an economic entity is at risk to become insolvent and then declared bankrupt.

However, the model has its limits and the authors do not claim that it can substitute other tools of financial analysis, requiring supplementary statistical or econometric instruments or procedures. Meanwhile, due to the fact that the data selection includes extremely accessible sets of information for the general public and, implicitly, for the business environment, it represents a readily available instrument, providing an accurate prediction tool with high applicability in real life situations.

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