APPLYING A PROPORTIONAL HAZARD MODEL TO THE FINANCIAL ANALYSIS OF BRAZILIAN CREDIT UNIONS

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ABSTRACT
Due to high interest rates and bank spreads, the number of credit unions in Brazil has increased over recent years. As financial institutions, these cooperatives need tools to signal impending financial problems. This paper focuses on one tool that can be used to evaluate credit union solvency: the Cox Proportional Hazards Model. A sample of eighty credit unions from the Brazilian state of Minas Gerais was selected to supply data. The analysis period is between December 2001 and June 2003. The results indicate that the relevant indicators for insolvency prediction are, in descending order of predictive ability, General Liquidity, Salary and Benefit Expenses, and the Loan/Equity Ratio. In general, results produced using the delineated theoretical model were in consonance with international literature.

KEY WORDS Insolvency, Cox’s proportional hazard model, credit unions.

INTRODUCTION
Credit unions, often called credit cooperatives, are financial institutions that promote thrift among their members, create a font of credit for these members, and play an important role in the economy of several countries. In Japan and Germany, about 35% of credit borrowings came from these institutions. In Europe, many important international banks began as cooperatives: Rabobank (Netherlands), DG Bank (Germany), and Caja Laboral Popular (Spain) (Geranegocios, 2004).

In Brazil, the number of credit unions and their total assets has increased over the last 20 years. There were 853 Brazilian credit unions in 1984, with total assets of R$ 656.62 millions (160 Euros). By 2001, these numbers had jumped to 1,302 and R$ 8.24 billions [2.03 Euros] (Leite, 2001). Over the same period, the number of Brazilian banking companies decreased from 271 to 208 (Leite, 2001). In 2003, there were 1,427 credit unions formally registered with Brazil’s Central Bank (OCEMG, 2004).

The number of Brazilian credit unions has increased for various reasons. According Berzoini and Souza (2001), one third of Brazil’s municipalities are without a bank agency, as large Brazilian banks determined that these municipalities cannot support a local branch. This lack has created an opening for credit unions to play important role in poor, small counties. Also, high interest and bank spreads forced small business owners and low income households to
organize credit unions. Leite (2001) reported that Brazilian banks have set the personal credit interest rate at about 8% a month while credit unions charge between 4.5% and 5% a month.

The credit cooperative system in Brazil is made up of two types of cooperatives: single and central. The single credit unions\(^1\) are autonomous financial institutions authorized and regulated by the Brazilian Central Bank. They are administered by their members and work very much as a banking agency. The central cooperative, whose members are the singles, is responsible for the coordination and inspection of all the affiliated singles’ operational processes. Central cooperatives also provide advice to their affiliated singles in regard to credit procedures and policies, technology procurement and training, accounting, marketing, communication, organization, and legal matters. The entire Brazilian cooperative system is made up of a network of interacting single agencies and central cooperatives.

Brazil’s cooperatives are subject to the same problems that face all businesses. They are sometimes created with little planning, which leads to staffing deficiencies and an inadequate support structure, and are exposed to damaging political interference and unbridled self-interest.

As financial institutions, Brazilian credit unions face the risks of the country’s financial system; the risks that come with being a financial intermediate in a developing country. The ability to efficiently manage financial risk will determine a cooperative’s survival in the competitive market. If the single cooperative, let alone the central cooperative, is structured to fail, the entire network can be prejudiced. It is therefore important that mechanisms are available to help identify high-risk cooperatives with accuracy and within a reasonable time-frame. This identification can be made using financial ratios.

The objective of this paper is to evaluate a Cox Proportional Hazards Model as a tool to assess the solvency of Brazilian credit unions. This will be accomplished by using the model to determine the survival probability and the solvency hazard of credit unions in a sample from the Brazilian state of Minas Gerais.

The paper contains three sections besides this Introduction. Section 2 presents the methodology used in the research, discussing the insolvency phenomena, control variables, Cox’s proportional hazard model, population, and sample. The results from this model are presented in Section 3. Finally, Section 4 contains the conclusion and suggestions for further research.

\(^1\) They are known as “credis”.
METHODOLOGY

The Cox Proportional Hazards Model

The Cox Proportional Hazards Model has been used to help in the financial evaluation of banks\(^2\), firms\(^3\), and cooperatives\(^4\). It can also provide early warning of pending financial institution insolvency or bankruptcy and assist decision makers when allocating resources. The Cox Proportional Hazards Model allows the determination of the probability of a credit cooperative’s failure.

Whalen (1991) discusses three advantages the Cox Proportional Hazards Model has over other risk modeling techniques, such as discriminant analysis and the Logit/Probit model: the Cox model can be used to generate the probable time to failure; it does not require set assumptions about the data’s distributional properties, and results from the Cox model are considerably more significant than results from the two noted alternative models. Lee and Urrutuia (1996) compared Logit and hazards models in their ability to predict the insolvency of property liability-insurers. They found that both models have the same accuracy, but hazard models identified more significant variables.

In the current study, “lifetime” refers to the time between the cooperative’s inception and the occurrence of the event: cooperative insolvency. The lifetime is adjusted by financial ratio co-variables.

The Cox model (Cox, 1972) can be described in the following form: \(T\) is the predicted time until a credit cooperative’s insolvency, and \(S(t)\), the survival function, is the probability that the cooperative will survive longer than \(t\) time period, with \(S(t)\) defined by

\[
S(t) = \Pr[T > t] = 1 - F(t)
\]  

(1)

where \(F(t)\) is the cumulative distribution function of the time to failure and the probability density function is \(f(t) = -S'(t)\). Even so, the insolvency time distribution can be represented by \(F(t)\) or \(f(t)\), and is described by the hazard function

\[
h(t) = \lim_{dt \to 0} \frac{P[t < T < t + dt / T > t]}{dt} = \frac{-S'(t)}{S(t)}
\]  

(2)


\(^3\) Martins (2003) e Minardi (2001)

\(^4\) Fully-Bressan (2002)
The hazard function, $h(t)$, is used to calculate the probability of insolvency in the next time period, given that the cooperative survives up to time $t$. According to Cox and Oakes, (1984), there are statistical advantages to be gained by using estimate $h(t)$ as opposed to $F(t)$ or $f(t)$. After the estimation of $h(t)$, the $F(t)$ and $f(t)$ estimates are obtained by

$$F(t) = 1 - \exp\left[-\int_0^t h(u)du\right] \quad (3)$$

and

$$f(t) = F'(t) \quad (4)$$

where $\int_0^1 h(u)du$ is the integrated hazard function, which is a basic tool used to test model variables for aptness.

There are different types of hazard models, settled in accord with the nature of the insolvency time distribution hypothesis. The proportional hazard model assumes the form

$$h(t/X, \beta) = h_0(t) \Psi(X, \beta) \quad (5)$$

Where, on the left side of the equation, $h(t/X, \beta)$ is the hazard function of a cooperative in time $t$; $X$ is a collection of variables that is considered to affect the likelihood of insolvency; and $\beta$ is the coefficient that describe how the variable affects the insolvency probability and will be estimated. On the equation’s right side, $h_0(t)$ and $\Psi(X, \beta)$ are, respectively, nonparametric and parametric parts. The nonparametric function is the baseline hazard probability and depends only on time.

In the Cox Proportional Hazard Model, $\Psi(X, \beta)$ assumes the exponential form, $e^{X\beta}$, as represented in (6).

$$S(t/X, \beta) = h_0(t)e^{(X/\beta)} \quad (6)$$

To determine the probability that a cooperative will survive longer than some given time into the future, the related survival function is given by

$$S(t/X, \beta) = S_0(t)e^{(X/\beta)} \quad (7)$$

where
\[
S(t) = \exp\left[-\int_{0}^{1} h_0(u)du\right]
\]  
(8)

with \(\int_{0}^{1} h(u)du\) denominated as the baseline integrated hazard function.

If explanatory variables have been centralized so that a cooperative with \(X = 0\) has the same ratio values as the mean of the population, then \(h_0(t)\) can be considered as the hazard function for an “average” cooperative in the population.

To run the model, samples of both financially solvent and insolvent cooperatives are needed and the time period before insolvency must be defined for both samples. Using these inputs, the baseline probability can be obtained; and from the estimated coefficients, the survival function can be determined by substituting coefficients of the relevant variables into equation (8).

**PROCEDURES AND DEFINITION OF VARIABLES**

Almeida (1993) maintains that the probability of bankruptcy can be estimated in four steps: (1) Define a range of solvent and insolvent firms; (2) Select variables that represent the solvency phenomena using the firms’ balance sheets; (3) Define a set of statistical procedures that can be used to model the balance sheets’ variables; and (4) Validate the model to verify its ability to forecast correctly. The author emphasizes the role played by the definition of failure criteria.

Kanitz (1978) notes that insolvent firms present insolvency signals long before bankruptcy occurs. By identifying these signals it could be possible to forecast financial failure before it occurs. Dietrich (1984) observed that a model to forecast insolvency would be based on a set of relevant statistical relationships between a firm’s financial ratios and potential or actual insolvency. The model’s objective would be to verify if the chosen account indicators signal the financial perspective of the firm.

According to Emery and Finnerty (1997, p. 880), insolvency occurs when a firm is not able to pay its debts. The authors distinguish between technical insolvency and bankruptcy. The first occurs due to a lack of cash, and the second “occurs when the firm’s total liabilities exceed the fair market value of its total assets.” Similarly, Altman (1968) considers that firm
insolvency occurs when the shareholders receive profitability lower than alternatives supplied by the market under similar conditions. Matias and Siqueira (1996) classified a bank as insolvent if it was in intervention or liquidation by the Brazilian Central Bank.

A firm presenting negative equity can also be considered insolvent. In the case of a credit union, negative equity means that if all assets of the credit union were liquidated, the amount received would not pay the liabilities. This concept was used by Janot (1999) when he concluded that identification of a financial institution as a likely candidate for failure by bank regulatory agencies is a signal of insolvency.

Because of the small number of credit unions that went bankrupt as defined by the criteria noted above over our study’s analysis period, it was necessary to add one criterion to the definition of “insolvent” provided by the cited authors. This added criterion is based in the Brazilian Central Bank’s Resolution 2.804/200, which states that financial institutions must avoid an imbalance between negotiable assets and obligatory liabilities. To implement this resolution, CECREMGE\(^5\) created a compulsory liquidity reserve percentage (Table 1) that defines a minimum balance that the credit unions must hold in cash. This study considers as insolvent those cooperatives that were obligated to hold 35% of their deposits in reserve.

<table>
<thead>
<tr>
<th>Table 1 – Reserve requirement percentage defined by CECREMGE</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Parameters</strong></td>
</tr>
<tr>
<td>Obligatory reserve</td>
</tr>
<tr>
<td>Additional reserves needed if:</td>
</tr>
<tr>
<td>- Deposits greater than equity</td>
</tr>
<tr>
<td>- Relation between the average of the volume anticipated</td>
</tr>
<tr>
<td>to the customers and deposits</td>
</tr>
<tr>
<td>- Negative monthly results</td>
</tr>
<tr>
<td>- Applications concentrated among the top 10 investors.</td>
</tr>
<tr>
<td>- Check devolution index</td>
</tr>
<tr>
<td>- Loans greater than 10% of the equity.</td>
</tr>
<tr>
<td>Penalty (for specific cases)</td>
</tr>
</tbody>
</table>

Source: CECREMGE (2004) adapted by the authors.

**DEFINITION OF CONTROL VARIABLES**

\(^5\) As explained in the Introduction, the central cooperative, CECREMGE (Minas Gerais Credit Union Central), is the main organization responsible for credit unions.
There are different approaches to determining financial institution solvency. In general, they focus the following financial aspects: amount and duration of delinquent loans, available reserves, sources and availability of operating funds, book and market value of assets, and current and expected operating expenses. From a different tack, Backer and Gosman (1978) concentrated on a financial institution’s use of outside resources to evaluate its solvency. Through debentures analysis, they correlate financial strength with the amount of commercial credit available to the institution and the institution’s total debt to other financial institutions.

Table 2 presents a summary of the explanatory variables used in the current research. The following papers analyzing bank insolvency or failure inspired the selection of our study’s variables: Altman (1968), Kanitz (1978), Matias and Siqueira (1996), Rocha (1999), Fully-Bressan (2002), and Martins (2003).

### Table 2 – Variable definitions and transformations

<table>
<thead>
<tr>
<th>Group 1 – Capitalization ratios</th>
<th>Group 2 – Solvency ratios</th>
</tr>
</thead>
<tbody>
<tr>
<td>I. Capitalization = Equity/Real Liability</td>
<td>I. NCOE = Net Cash flow after operating expenses/Total flow</td>
</tr>
<tr>
<td>II. Fixed = Fixed Assets/ Equity</td>
<td>II. Coverage = Available income/ Real Liability</td>
</tr>
<tr>
<td>III. Turnover Capital = (Equity – Fixed Asset) / Equity</td>
<td>III. Liquidity = Current and long run Asset /Current and long run Liability</td>
</tr>
<tr>
<td>IV. Leverage = Total Revenue/ Equity</td>
<td>IV. Total loans/Equity = Total Loans/Equity</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Group 3 – Cost and expense ratios</th>
<th>Group 4 – Return ratios</th>
</tr>
</thead>
<tbody>
<tr>
<td>I. Personal expense = Salary and benefit expense/Total Revenue</td>
<td>I. Earnings = Operating Revenue /(Real Asset – Fixed Asset)</td>
</tr>
<tr>
<td>II. Administrative Expense = Operating Expense /Total Revenue</td>
<td></td>
</tr>
<tr>
<td>III. Total Expense = Total Expense/ Total Revenue</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Group 5 – Growth ratios</th>
<th>Definitions</th>
</tr>
</thead>
<tbody>
<tr>
<td>I. Total Loan Growth = Total Loan in time t / Total Loan in time t-1</td>
<td>I. Real Asset = Total Asset – Inter Financial Relations – Interdependency Relations</td>
</tr>
<tr>
<td>II. Total Revenue Growth = Total Revenue in time t / Total Revenue in time t-1</td>
<td>II. Real Liability = Total Liability– Inter Financial Relations – Interdependency Relations</td>
</tr>
<tr>
<td>III. Operational Revenue Growth = Operating Revenue in time t/Operating Revenue in time t-1</td>
<td>III. Total Loans = Real Asset – Fixed Asset– Others</td>
</tr>
<tr>
<td></td>
<td>IV. Total Revenue = Real Liability – Equity – Others</td>
</tr>
</tbody>
</table>

Source: the authors

### POPULATION, SAMPLE, AND DATA
Data in our study are from five half-year balance sheets of eighty cooperatives that were patrons of the Central Minas Gerais Credit Union (CECREMGE) from December, 2001 through June, 2003: December 2001, June 2002, December 2002, June 2003, and December 2003. Minas Gerais has the greatest number of credit unions of all Brazilian States with about 290,204 enrolled members and 3,111 employees (OCEMG, *Cooperativismo*, 2004). The eighty cooperatives represent 68% of CECREMGE cooperative patrons.

According to the study’s criteria, 53 of the sampled cooperatives were grouped as solvent and 27 were grouped as insolvent (Table 3).

The sample consists not only of data from cooperatives whose time until insolvency (failure) is known, but also data from solvent cooperatives that had not failed through to June 2003, the end of the period of analysis. The data from cooperatives that had not failed during the study period are said to be censored. The statistical procedures were implemented using S-PLUS 2000 software.

For a solvent cooperative, the censored survival time is defined to be the time (in months) from June 2002 until the date of insolvency of its matched insolvent cooperative. Survival time for an insolvent cooperative is defined to be the time (in months) from June 2002 until the date of its insolvency (Table 3).

**Table 3 - Insolvency classification in the sample**

<table>
<thead>
<tr>
<th>Month</th>
<th>Number of insolvent cooperatives</th>
<th>%</th>
<th>Survival Time</th>
</tr>
</thead>
<tbody>
<tr>
<td>DEC – 2001</td>
<td>1</td>
<td>0.04</td>
<td></td>
</tr>
<tr>
<td>JULY – 2002</td>
<td>1</td>
<td>0.04</td>
<td>2</td>
</tr>
<tr>
<td>MAY – 2003</td>
<td>1</td>
<td>0.04</td>
<td>11</td>
</tr>
<tr>
<td>JUN – 2003</td>
<td>24</td>
<td>0.89</td>
<td>12</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>27</strong></td>
<td><strong>100.00</strong></td>
<td></td>
</tr>
</tbody>
</table>

Source: Research Results
MODEL ESTIMATION AND RESULTS

Comparison between models

To determine which of the 15 explanatory variables (ratios) presented in Table 2 are the best predictors of insolvency, a stepwise procedure combining forward and backward elimination is applied, following the same procedures of Lane et al. (1986). An equation for each explanatory variable was adjusted, and the significance of the variable to explain cooperative insolvency was tested at a 10% level using the Likelihood Ratio Test (LRT).

Consider, for example, that Models (9) and (10) were tested to determine which best explains the data set.

\[ M_1 - \exp\{ \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_p X_p \} \lambda_0(t) \]  
\[ M_2 - \exp\{ \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_p X_p + \beta_{p+1} X_{p+1} + \ldots + \beta_q X_q \} \lambda_0(t) \]

Model (9) is said to be in line with model (10), from the parametric perspective, if it contains a subset of the terms presented in (10). As the number of parameters in (10) is greater than the number of parameters in (9), it is expected that (10) presents better adjustment to the data set. But, it was also necessary to determine if the \( q \) additional terms in model M2 (10) are statically significant to explain the data set. If they are not significant, model M1 (9) is better fitted than M2 (10). A chi-square likelihood ratio test (LRT) of the significance of the overall model is used to select the model.

An equation for each explanatory variable listed in Table 2 was adjusted, and the significance of the variable to explain cooperative insolvency was tested at a 10% level using the Likelihood Ratio Test (LRT). By this criterion, the more relevant explanatory variables are Imobilization (IM), Capital Turnover (CT), General Liquidity (GL), Loans/Equity (L/E), Salary and Benefit Expense (SBExp), Mortise, and Operating Expense (OExp). Table 4 presents a summary of the estimation results.
Table 4 - Adjusted model summary results for each included variable

<table>
<thead>
<tr>
<th>Included Variable</th>
<th>-2LogL</th>
<th>LRT</th>
<th>P-value</th>
<th>LRT</th>
</tr>
</thead>
<tbody>
<tr>
<td>None</td>
<td>234.19</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Capitalization (CA)</td>
<td>232.74</td>
<td>1.45</td>
<td>0.23</td>
<td></td>
</tr>
<tr>
<td>Imobilization (IM)</td>
<td>230.59</td>
<td>3.61</td>
<td>0.06</td>
<td></td>
</tr>
<tr>
<td>Capital Turnover (CT)</td>
<td>230.59</td>
<td>3.61</td>
<td>0.06</td>
<td></td>
</tr>
<tr>
<td>Leverage (LE)</td>
<td>233.79</td>
<td>0.41</td>
<td>0.52</td>
<td></td>
</tr>
<tr>
<td>NECOE</td>
<td>228.20</td>
<td>5.99</td>
<td>0.01</td>
<td></td>
</tr>
<tr>
<td>Coverage (CO)</td>
<td>233.89</td>
<td>0.31</td>
<td>0.58</td>
<td></td>
</tr>
<tr>
<td>General Liquidity (GL)</td>
<td>221.92</td>
<td>12.27</td>
<td>0.00</td>
<td></td>
</tr>
<tr>
<td>Loans/Equity (L/E)</td>
<td>227.16</td>
<td>7.03</td>
<td>0.01</td>
<td></td>
</tr>
<tr>
<td>Salary and Benefit Expense (SBExp)</td>
<td>224.57</td>
<td>9.63</td>
<td>0.00</td>
<td></td>
</tr>
<tr>
<td>Operating Expense (Oexp)</td>
<td>227.58</td>
<td>6.61</td>
<td>0.01</td>
<td></td>
</tr>
<tr>
<td>Total Expense (TExp)</td>
<td>233.92</td>
<td>0.27</td>
<td>0.60</td>
<td></td>
</tr>
<tr>
<td>Income Generation (Igen)</td>
<td>233.49</td>
<td>0.70</td>
<td>0.40</td>
<td></td>
</tr>
<tr>
<td>Total Aplication Growth (TAG)</td>
<td>234.11</td>
<td>0.08</td>
<td>0.77</td>
<td></td>
</tr>
<tr>
<td>Total Deposit Growth (TCG)</td>
<td>234.11</td>
<td>0.09</td>
<td>0.77</td>
<td></td>
</tr>
<tr>
<td>Operating Earning Growth (OEG)</td>
<td>234.14</td>
<td>0.05</td>
<td>0.83</td>
<td></td>
</tr>
</tbody>
</table>

Source: Research Results

As multicolinearity was verified between the variables Immobilization and Capital Turnover, Immobilization was not included in the model. After this exclusion, the candidate variables to explain the insolvency hazard in descending explicative order, at 10% of probability, are: General Liquidity, Salary and Benefit Expense, Loans/Equity, Operating Expenses, NECOE, and Capital Turnover.

Beginning with two most significant variables identified by LRT test, General Liquidity (GL) and Salary and Benefit Expense (SBExp), other variables are included in the model and the combined explanatory power of the included variables is tested. The decision rule is to select a model that presents the lower LTR values. It can be concluded that the variables General Liquidity (GL), Salary and Benefit Expense (SBExp), and Loans/Equity Ratio (L/E) had the greatest effect on cooperative credit union insolvency in the state of Minas Gerais (Table 5).

Table 5 - Model selection

<table>
<thead>
<tr>
<th>Model</th>
<th>Explanatory Variables</th>
<th>-2LogL</th>
<th>LRT</th>
<th>P-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>M I</td>
<td>GL+SBExp</td>
<td>214.12</td>
<td></td>
<td></td>
</tr>
<tr>
<td>M II</td>
<td>GL+SBExp+ L/E</td>
<td>209.78</td>
<td>4.34</td>
<td>0.04</td>
</tr>
<tr>
<td>M III</td>
<td>GL+ SBExp + L/E +OExp</td>
<td>209.71</td>
<td>0.07</td>
<td>0.79</td>
</tr>
<tr>
<td>M IV</td>
<td>GL+ SBExp + L/E +MO</td>
<td>208.25</td>
<td>1.53</td>
<td>0.22</td>
</tr>
<tr>
<td>M V</td>
<td>GL+ SBExp + L/E +CT</td>
<td>209.26</td>
<td>0.52</td>
<td>0.47</td>
</tr>
</tbody>
</table>

Benefit Expense (SBExp), General Liquidity (GL), Loans/Equity (L/E), Capital Turnover (CT), Mortise (MO), Salary and Benefit Expense (SBExp), and Operating Expense (OExp).
There are two graphic techniques commonly used to check the “goodness” of a Cox model’s fit, shown in Figures 1 and 2. The Cox model assumes that the hazard function \( h(t) \) is directly related to the hazard baseline function, \( h_0(t) \), as an \( e \) potency, represented in (6). Figure 1 (below) is used to check this assumption. If the hazards are proportional, the Log Minus Log (LML) graphs need to be parallels. As the graphs in Figure 1 show that General Liquidity (GL), Salary and Benefit Expense (SBExp), and Loans/Equity Ratio (L/E) are continuous variables, they were transformed into dummy variables, assigning the value 1 to observations below the median and zero for observations above the median.

Figure 1 shows that the proportional hazard assumption was attended to because the Log Minus Log (LML) graphs present parallel shapes.

Figure 1 –Log minus Log function of model variables

(a) General Liquidity (GL)

(b) Salary and Benefit Expense (SBExp)

(c) Loans/Equity Ratio (L/E).

Source: Research Results
Another graphic technique used to verify model fitness is based on observations of the fitted model’s residuals plotted against the failure time order. The plots for the models of three variables are presented in Figure 2. As shown, the residuals are distributed randomly around zero value. Plots indicate strong evidence that the model has a good fitness to describe the failure time.

**Figure 2 – Failure time order of each model variable**

![Figure 2](image)

(a) General Liquidity  
(b) Salary and Benefit Expense (SBExp)  
(c) Loans/Equity Ratio

Source: Research Results

**Explaining the insolvency hazard**

Table 6 presents estimation results from the selected model. The Table gives the estimate for each variable’s coefficient, the standard error of this estimate, the probability level that the population coefficient is equal to zero, its relative hazard value (that is a measure of the contribution of the individual variable to the predictive power of overall model), and the confidence interval at 90% of probability. The results show that all coefficients in the model are significant and that the individual variables have a high degree of predictive ability.
The General Liquidity indicator is shown to play an important role in the determination of credit union insolvency. The negative sign of this indicator’s $\beta$ coefficient in Table 6 indicates that an increase in the General Liquidity ratio is associated with a decrease in the probability of insolvency: an increase of one unity in the GL ratio implies a 0.33 decrease in the probability of insolvency.

<table>
<thead>
<tr>
<th>Covariate</th>
<th>Coefficient ($\beta$)</th>
<th>Standard Error</th>
<th>P Value</th>
<th>Relative Hazard (RH)</th>
<th>IC (RH, 95%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>General Liquidity</td>
<td>-1.112</td>
<td>0.5691</td>
<td>0.05</td>
<td>0.0329</td>
<td>(0.0108; 1.0000)</td>
</tr>
<tr>
<td>Salary and Benefit Expenses</td>
<td>29.745</td>
<td>8.8873</td>
<td>0.00</td>
<td>1.3500*</td>
<td>(1.2505; 3.0420)*</td>
</tr>
<tr>
<td>Loans/Equity</td>
<td>0.118</td>
<td>0.0574</td>
<td>0.04</td>
<td>1.1200</td>
<td>(1.0100; 1.2600)</td>
</tr>
</tbody>
</table>

*Relative Hazard is calculated by considering an increase of 0.01 unit Salary and Benefit Expenses

Source: Research Results

Another indicator found to be of use when forecasting solvency was Salary and Benefit Expenses, which is a measure of the resources used to manage the cooperative. As our results show, an increase of 0.01 in the Salary and Benefit Expenses variable is associated with a 1.3500 increase in the probability of insolvency. Although it represents a large reaction, the result is compatible with the average 0.02 value of the ratio during the study period: Salary and Benefit Expenses were, on average, 2% of total studied credit union deposits. If this ratio increases to a unit, the cooperative will be spending more on operating expenses than it is receiving in deposits.

Finally, the Loans/Equity variable was examined to determine its correlation with credit cooperative solvency. A high Loan/Equity ratio signals a problem should cooperative members fail to repay loans made by the cooperative, especially if the cooperative concentrates its resources in loans made to a few, un-creditworthy members. An increase of one unit in this indicator is associated with an increase of 1.12 in the insolvency hazard (Table 4). The average Loans/Equity ratios for solvent and insolvent cooperatives in 2003 were 1.92 and 6.07 respectively. On the average, members of insolvent cooperatives are demanding a volume of credit six times greater than their cooperative’s equity.

6 In the account sheets of the analyzed cooperatives, it was not possible to differentiate between short and long run, besides liquidity is a firm’s short run ratio.
Evaluation of the survival probability of the cooperatives

The estimated model can be used to generate the probability that a cooperative will survive longer than $t$ time units. In this calculation, the estimated parameters, the relevant variable values, and the baseline survival probability $S_0(t)$ are substituted in (7).

The survival profiles of a typical solvent and a typical insolvent cooperative are presented in Figure 3, with the top line being the survival profile for a typical solvent cooperative. This line is obtained by inserting the average values of selected variables from the sample’s solvent cooperatives into the estimated survival function. The lower line (green) shows the survival profile of the sample’s insolvent cooperatives, and was obtained using the same procedure as was used to generate the solvent cooperatives’ profile.

**Figure 3 – Survival profiles for solvent and insolvent cooperatives**

The vertical distance between the lines represents the estimated reduction in survival probability for the insolvent cooperatives relative to the solvent ones at every time horizon. It can be inferred that the survival probability of the typical insolvent cooperative is lower than that probability for the typical solvent cooperative at every time horizon. The hazard seems to be constant at any specific time because it is a proportional hazard model.

The survival function, graphed in Figure 4, presents survival probabilities of the average Minas Gerais credit union through specific time periods. It was found that an average credit union in the state of Minas Gerais had a 97.9% probability of solvency through month 1, a
97.1% probability of solvency through month 2, and a 72.1% probability of solvency through month 13 of the study.

**Figure 4 – Survival probability of the cooperatives**

![Survival Function at mean of covariates](image)

Source: Research Results

As opposed to the survival function, the cumulative hazard function graphed in Figure 5 presents insolvency probabilities after specific time periods. Using this function, an average cooperative in the state of Minas Gerais was found to have a 2.1% probability of insolvency through month 1, a 2.9% probability of insolvency through month 2, and a 32.7% probability of insolvency through month 13.

**Figure 5 – Survival Hazard Probability of the cooperatives**

![Hazard Function at mean of covariates](image)

Source: Research Results
Evaluating classification results

Given the values for a particular cooperative’s explanatory variables, the Cox model can be used for prediction or classification through calculation of the probability that the cooperative will survive longer than \( t \) months. If the probability of survival is less than some cutoff value, then the cooperative is classified as a “possible insolvent.” The cutoff value is determined as in Lane, Looney and Wansley (1986, p. 524), Whalen (1991, p.27), Rocha (1999, p. 148), and Martins (2003, p. 58). This critical value is obtained by taking a random sample of cooperatives and then calculating the ratio of solvent cooperatives in the sample to the total number of cooperatives in the sample \( (53/(27+53) = 0.66) \). In sequence, the survival probabilities of each cooperative are then compared with the cutoff value. If the survival probability of the cooperative is lower than the cutoff value, it is classified as a possible insolvent.

Errors in classification analysis are either Type I or Type II. In our study, a Type I error is one in which the model does not indicate as insolvent a cooperative that is actually insolvent. A Type II error occurs when the model indicates that an actually solvent cooperative is insolvent.

According to Whalen (1991), a good model should have low incidence of Type I errors. A high incidence of Type I errors indicates that the model probably has delayed resolution, low resolution, or both. Lane et al. (1986, p. 526) affirm that “a Type I error is more important in an early warning system than either total classification accuracy or a Type II error.” A Type II error should be cautiously analyzed, as it may turn out to be a good indicator of the model’s predictive ability, especially if the cooperative fails in the relatively near future.

Table 7 presents the current study’s results for \( t \) equal to the all periods in the 13 months of our study, when the greatest number of cooperatives in our sample had become insolvent. Solvent and insolvent classification accuracy is 83% and 70% respectively, with an overall accuracy of 79%
Table 7 – Cox model classification accuracy for a 13 month time horizon

<table>
<thead>
<tr>
<th>OBSERVATIONS</th>
<th>SOLVENT</th>
<th>INSOLVENT</th>
</tr>
</thead>
<tbody>
<tr>
<td>ACTUAL</td>
<td>53</td>
<td>27</td>
</tr>
<tr>
<td>COX TEST CORRECT</td>
<td>44</td>
<td>19</td>
</tr>
<tr>
<td>COX TEST INCORRECT</td>
<td>$8^K$</td>
<td>$9^{KK}$</td>
</tr>
<tr>
<td>% CORRECT W/COX TEST</td>
<td>83 % (44/53)</td>
<td>70 % (19/27)</td>
</tr>
<tr>
<td>TOTAL</td>
<td></td>
<td>79% [(44+19)/80]</td>
</tr>
</tbody>
</table>

Source: Research Results

The percentages of Type I and Type II errors were not satisfactory. Type I errors are a greater problem because they cause management indecision and hamper problem resolution. Type II errors are less problematic, as they may be indicators of future negative financial performance. CECREMGE agents and the managers of the nine studied cooperatives for which the model made a verified Type II error need to closely monitor the evolution of these cooperatives’ General Liquidity (GL), Salary and Benefit Expense (SBExp) and Loans/Equity Ratio (L/E) indicators.

SUMMARY AND CONCLUSIONS

Study results show that the Cox Proportional Hazards Model is a helpful tool for the analysis of financial distress in credit unions, which can provide information regarding the expected time until insolvency. The model can be used to identify variables that have a significant impact on credit union solvency and to describe the relationship between these explanatory variables and solvency.

It was found that the more significant variables affecting credit union insolvency are, in descending order of significance, General Liquidity, Salary and Benefit Expense, and the Loans/Equity Ratio. Estimation results measure the impact of changes in these variables on the probability of insolvency.

The sample is significant in relation to the population studied, and the model presents a regular fitness coefficient measure, 79%. Type I and II errors are 30% and 17% respectively. Type II errors should be carefully analyzed because they provide an early warning of high risk cooperatives. Type II errors indicate that nine credit unions (7.6% of the CECREMGE patron...
cooperatives) will fail in the near future. Managers of these nine credit unions need to be alert and carefully monitor the significant ratios.

The organizational structure of the Brazilian credit union system makes bankruptcy for the single cooperative difficult. In order to include more insolvent credit cooperatives in our study, it was necessary to add the “35% reserve requirement” to the standard criteria for determining insolvency. This addition made it was more difficult to adjust the model. Future research could create other parameters to classify credit unions as insolvent.

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