行政院國家科學委員會專題研究計畫　成果報告

應用灰色理論構建信用卡債權證券評選與評價模式

計畫類別：個別型計畫
計畫編號：NSC92-2416-H-263-002-
執行期間：92 年 08 月 01 日至 93 年 07 月 31 日
執行單位：致理技術學院財務金融系(科)

計畫主持人：楊適伃

報告類型：精簡報告

處理方式：本計畫可公開查詢

中　華　民　國 93 年 10 月 28 日

行政院國家科學委員會補助專題研究計畫 ■ 成 果 報 告
□期中進度報告

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計畫類別：■ 個別型計畫　□ 整合型計畫
計畫編號：NSC 92 － 2416 － H － 263 － 002 －
執行期間：2003 年 08 月 01 日至 2004 年 07 月 31 日

計畫主持人：楊適伃
共同主持人：
計畫參與人員：楊謹先、葉思儀

成果報告類型(依經費核定清單規定繳交)：■ 精簡報告　□完整報告

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執行單位：致理技術學院財務金融系
中　華　民　國　九十三　年　七　月　三十一　日

摘　　要

本研究運用灰色理論，建構一個信用卡債權證券評選與評價模式，找出影響信用卡逾期還款、違約、動用循環信用及預借現金之因素，並以此來篩選及群組信用卡債權證券中之信用卡戶。本研究之主要研究結果如下：

(一) 本研究以邏輯迴歸(logistic regression model)，對影響信用卡逾期還款、違約、動用循環信用及預借現金之因素進行分析。發現台灣信用卡市場中，影響信用卡逾期還款、違約、動用循環信用及預借現金之主要因素包括：持卡人之年齡、收入、教育程度、性別、職業及過去信用紀錄。

(二) 本研究運用所找出之影響信用卡還款情形之因素及灰色關聯分析，來替金融機構篩選信用卡債權證券中之信用卡戶。

本文研究結果可提供金融機構信用卡債權證券發行部門經理人，作為訂定信用卡債權證券價格之參考。

關鍵詞：信用風險、信用卡、灰色理論、信用卡債權證券

Abstract

This paper applies Grey theory to construct a new assessment and valuation model of Credit Card Asset Backed Securities. The main results as follows:

1. This paper applies the logistic regression model to analyze the influence of factors on abnormal payment, revolving and cash advances. Analytical results indicate that the following factors are significant in explaining abnormal payments, revolving and cash advances: age, income, educational level, gender, occupation and previous credit.
2. This paper applies a novel approach, grey relational analysis, to assess credit card applications and pick out appropriate credit card applications into credit card asset backed securities（Credit Card ABS）pools.

Taiwanese financial institutions can use the results from this paper when pricing the prices for credit card asset backed securities（Credit Card ABS）.

Keywords：Credit Risk, Credit Cards, Grey Theory, Credit Card Asset Backed Securities (Credit Card ABS)

報告內容

1. INTRODUCTION

The credit card asset backed securities (Credit Card ABS) is a new business of the financial system in Taiwan. Abnormal payments (i.e. delinquent, and default), revolving and cash advances of credit card make it difficult for financial institutions to regulate funds, to predict cash flow of credit card ABS pools, and can even cause losses. Financial institutions want to know and manage credit card loans that will possibly become delinquent and /or default, and/or revolving and/or cash advances. Financial institutions must have an appropriate method to pick out appropriate credit card applications into credit card asset backed securities pools.

Credit card and mortgages are the similar business. Previous methods to select credit card applications and home mortgages loans included the discriminant analysis model (Altman, 1968; Grablowsky and Talley, 1981; Steennckers and Goovates, 1989), the linear regression model and the logistic regression model (Martin, 1977; Platt and Platt, 1991; Smith and Lawrence, 1995), the analysis hierarchy process (AHP) (Srinivasan, 1987), and the neural network and expert system (Altman, Marco and Varetto, 1994; Desai, Crook and Overstreet, 1996). Above Methods classified credit card applications by constructing a large database. As a result, they were difficult to implement when credit card asset backed securities business commences or past loan data were not properly conserved. Previous models were also trouble because they required large historical data and also had an intricate calculating process that was difficult to use. This paper applies the grey relational analysis to pick out credit card applications into credit card asset backed securities pools in order to overcome such weaknesses.

The grey relational analysis has the following advantages over previous models: relatively little data is required, simple mathematics during the calculation, and discontinuous variables can be manipulated. The logistic regression model is generally preferred over other methods when select credit card applications and home mortgage applications (Thomas, 1998). This paper will compare the grey relational analysis to the logistic regression model to pick out credit card applications into credit card asset backed securities polls.

Succeeding sections describe the methodology, data source, empirical results, and conclusions.

2. METHODOLOGY

2.1 Grey Relational Analysis

Grey relational analysis is an effective means of analyzing the relationship between two series. This paper applies grey relational analysis to calculate the grey relational coefficients between the candidate credit card applications and the ideal appropriate credit card applications. Suitable credit card applications can be picked out into credit card asset backed securities pools according to grey relational coefficients. The algorithm of grey relational analysis is illustrated as follows :

(1) Data processing

Before calculating the grey relational coefficients, data of the series must be dealt with. Where $\max_{\forall k} X_i(k)$ is the maximum value of entity k, $\min_{\forall k} X_i(k)$ is the minimum value of entity k and $X_{ob}(k)$ is the objective value of entity k.

Three kinds of situations and data processing are as follows:

1) Upper-bound effectiveness measuring (i.e., larger-the-better)

$$X_i^*(k) = \frac{X_i(k) - \min_{\forall k} X_i(k)}{\max_{\forall k} X_i(k) - \min_{\forall k} X_i(k)} \tag{1}$$

2) Lower-bound effectiveness measuring (i.e., smaller-the-better)

$$X_i^*(k) = \frac{\max_{\forall k} X_i(k) - X_i(k)}{\max_{\forall k} X_i(k) - \min_{\forall k} X_i(k)} \tag{2}$$

3) Moderate effectiveness measuring (i.e., nominal-the-best)

If $\max_{\forall k} X_i(k) \geq X_{ob}(k) \geq \min_{\forall k} X_i(k)$

$$X_i^*(k) = \frac{\left|X_i(k) - X_{ob}(k)\right|}{\max_{\forall k} X_i(k) - \min_{\forall k} X_i(k)} \tag{3}$$

(2) Calculate the grey relational coefficients

Let X_0 be the referential series with k entities and X_i be the comparative series with k entities, $i = 1,2,...,892$; $k = 1,2,...,6$.

That is,

$$\begin{aligned}
X_0 &= \{X_0(1), X_0(2), ..., X_0(6)\} \\
X_1 &= \{X_1(1), X_1(2), ..., X_1(6)\} \\
X_2 &= \{X_2(1), X_2(2), ..., X_2(6)\} \\
&\vdots \\
X_{3528} &= \{X_{892}(1), X_{892}(2), ..., X_{892}(6)\}
\end{aligned}$$

The grey relational coefficients between the referential series of X_0 and the comparative series X_i is defined as follows :

$$\Gamma_{0i} = \frac{\Delta_{\min} + \Delta_{\max}}{\Delta' + \Delta_{\max}}$$

Where $\Delta' = \sqrt{\sum_{k=1}^{n} \left(\frac{\Delta_{0i}^2(k)}{n^2} \right)}$; $\Delta_{0i}(k) = \left| X_0(k) - X_i(k) \right|$; $\Delta_{\max} = \max_{\forall i} \max_{\forall k} \Delta_{0i}(k)$; $\Delta_{\min} = \min_{\forall i} \min_{\forall k} \Delta_{0i}(k)$.

Let $X_i = \{X_i(1), X_i(2), ..., X_i(k)\}$ denote the *i*-th application and $X_0 = \{X_0(1), X_0(2), ..., X_0(k)\}$ represent the ideal poor application. Herein, the grey relational coefficient (Γ_{0i}) between X_0 and X_i is calculated. The value of Γ_{0i} is close to 1, indicating that the *i*-th credit card application is a suitable one. In the empirical test, when Γ_{0i} >0.75, we predict that the application will be an appropriate one into the credit card asset backed securities. When Γ_{0i} <0.75, we predict that the application is a poor loan. Herein, Eq. (4) is used to calculate the predictive accuracy.

$$\text{Predictive accuracy} = \left(\frac{100}{N}\right) \times \sum_{i=1}^{n} Z_i \tag{4}$$

Where $N =$ the sample sizes; $Z_i = 1$, when the credit card application is accurately predicted; $Z_i = 0$, when the credit card application is not accurately predicted.

2.2 Logistic regression model

Denote a set of six predictors for a binary response Y by $X_1, X_2, ..., X_6$. $Y = 1$ denote that the application is an appropriate one. The logit of the probability π that $Y = 1$ can be expressed as follows:

$$\text{logit}(\pi) = \alpha + \beta_1 X_1 + \beta_2 X_2 + ... + \beta_6 X_6$$

$$\pi = \frac{\exp(\alpha + \beta_1 X_1 + \beta_2 X_2 + ... + \beta_6 X_6)}{1 + \exp(\alpha + \beta_1 X_1 + \beta_2 X_2 + ... + \beta_6 X_6)}$$

Herein, credit card application data are used to implement the logistic regression model. In doing so, values of $\alpha, \beta_1, \beta_2, ...,$ and β_6 are used. In addition, the logistic regression model is applied to calculate the probability π of the loan. When $\pi \geq 0.5$, we predict that the loan will be a suitable one. Herein, Eq. (4) is used to calculate the predictive accuracy.

3. The Data

3.1 Data source

This paper adopts the data from credit card applications obtained by a major financial institution in Taiwan stretching from July 1, 1998 to June 30, 2000. 892 credit card applications are selected by random and all incomplete data is deleted.

3.2 Variables in the grey relational analysis and logistic regression model

The six variables selected to explain abnormal payments, revolving and cash advances are: age, income, educational level, gender, occupation and previous credit.

4. Results

4.1 grey relational model results

The grey relational analysis is employed to predict appropriate applications as summarized by Table 1.

Since 701 appropriate loans are correctly forecast and pick out into credit card asset backed securities. 701/ (701+56) = 92.60% of appropriate applications are labeled precisely. Since 33 not appropriate applications are correctly forecast 33/ (102+33) = 24.44% of not appropriate applications are classed precisely. The average weighting accuracy of predicting appropriate applications into credit card asset backed securities is 82.29%.

The above results attest that the grey relational analysis can very accurately predict appropriate credit card applications. Financial institutions can use the grey relational results to pick out credit card applications and refuse poor applications.

Table 1 Grey relational analysis predictions

Predicted Observed	Appropriate (1)	Not Appropriate (0)	Percentage of accuracy	Overall accuracy
Appropriate (1)	701	56	92.60%	82.29%
Not Appropriate (0)	102	33	24.44%	

4.2 Logistic regression model results

Table 2 summarizes the logistic regression model predictions: 679/ (679+78) = 89.70% of appropriate applications are classed correctly because 679 appropriate applications are precisely forecast. 30/ (105+30) = 22.22% of not appropriate applications are labeled precisely since 30 not appropriate applications are correctly forecast. The average weighting accuracy for appropriate applications is 79.48%, while 89.70% of appropriate application and 22.22% of not appropriate application are labeled precisely.

Table2 Logistic regression model predictions

Predicted / Observed	Appropriate (1)	Not Appropriate (0)	Percentage of accuracy	Overall accuracy
Appropriate (1)	679	78	89.70%	79.48%
Not Appropriate (0)	105	30	22.22%	

4.3 Comparison of results

The grey relational analysis and logistic regression model can both precisely predict and pick out appropriate credit card applications into credit card asset backed securities pools. The prediction accuracy of the grey relational analysis is 82.29% (as listed in Table 1), while the logistic regression model is accurate 79.48% of the time. About 80% of the applications are classed correctly.

5. Conclusions and Policy Implications

This paper develops a novel means of picking out suitable credit card applications into credit card asset backed securities pools. Logistic regression model has been the conventional means of selecting credit card applications. However, the logistic regression model is difficult to implement. Results in this paper demonstrate that grey relational analysis is a viable alternative. The prediction accuracy of grey relational analysis is 82.29%. The accuracy of logistic regression model is 79.48%. According to our results, grey relational analysis has higher prediction accuracy than the logistic regression model. Credit card asset backed securities is a new business for Taiwan’s financial institutions. Smaller than multinational financial institutions, Taiwan’s financial institutions do not have an adequate number of professionals and sufficient data to construct a pick out and predictive model. Grey relational analysis does not require any professionals and a significant amount of data and, therefore, appropriate for Taiwan’s financial institutions.

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計畫成果自評

本研究目的為提出信用卡債權證券評選與評價模式，以協助金融機構房貸證券發行部門的經理人，對即將發行之信用卡債權證券進行合理的評價。本研究內容與原計畫大致相符，且達成預定完成之目標，唯一的缺憾是評價模式因資料稀少，未有實例加以驗證，待後續研究持續努力。

信用卡債權證券在我國有多家銀行有意發行，對於信用卡債權證券之相關研究付之闕如，全面移植國外之經驗來評價信用卡債權證券，恐怕價格有所失真。因此，我們有必要依據國內持卡人之還款及預借現金情形，來評價我國信用卡債權證券之價值。此一研究可使學術界在信用卡債權證券相關問題上有進一步的瞭解；同時對於我國發展信用卡債權證券市場也有很大的貢獻。此