Bank Lending Strategy in The Stock Market

Dissertation Abstract

Bank Lending Strategy in The Stock Market

Graduate School of
Natural Science and Technology
Kanazawa University

Division of Mathematical
and Physical Sciences

Computational Science

School registration No.: 1223102010
Name: Tristiyanto
Date Submission: July 1^{st}, 2015

1 Introduction

Margin trading is stocks trading using loan leverage from a financial institution; in here we call a bank. It is beneficial for improving liquidity in the market and creating smooth price formation of the stock. However, margin trading has a tendency to escalate the price. As the price of the stocks increases drastically, the authority then raises the minimum margin or minimum collateral to mitigate the risk. Theoretically it will slow down the price movement. Unfortunately, the market reaction result is different. Most of them sell their stocks, so the price then collapses. It was what happen in US great depression in 1929 and lost decade in Japan 1990.

For bank or lender, increasing margin requirements is an effective tool to mitigate the risk. However, good investors usually also being filtered out by it, as margin requirement only keep investors who have good working capital but, unfortunately, are incompetent to predict good performance investor.

In this study, we develop a new method for using credit scoring to predict an investors' performance when trading on the margin. Compared to a margin requirement that screens investors merely by their capital and collateral, credit scoring can extend the scope of the evaluation to include the character, capacity and condition of the trader. The simulation presented here was developed from the stock market simulation that was studied by Nakatani et al. [7, 9] and Zhu [15]. The bank agent in that model did not have intelligence and considered only the ratio of debt to working capital. We implemented an artificial intelligence approach to credit scoring for granting loans. We used a statistical method, multiple discriminant analysis [1] and artificial neural networks, decision trees and support vector machines to create our credit-scoring schema.

In the financial industry, credit scoring is well known as a way to predict bankruptcy and thus our research appears to be similar to that of others; however, to the best of our knowledge, there have been no scientific studies of using credit scoring for margin trading. Most of the related research considers ways to predict bankruptcy of companies [3, 4, 5, 6, 10, 11, 14]. However, Wang [13] used an analytical approach to measuring the credit risk for margin trading and calculated the threshold-breaking probability, the default probability and loss given default. In that study, financial ratios were not used to predict bankruptcy, whereas we use the investors' financial ratios and an artificial intelligence approach to predict the status of each investor. We developed a method for credit scoring that uses three classes ("bankrupt", "surviving" and "profitable"), although most known methods use only two classes ("bankrupt" and "surviving" or good and bad). The "profitable" class is useful for maintaining market liquidity when a bubble occurs. Banks can deliver their loans to investors who will help maintain market liquidity. We consider the impact of credit scoring on price movement and its effect on controlling bubbles.

We also present a new banking strategy for taming bubbles [8]. Most economists use financial regulations and macroeconomic policies in their attempts to tame the crashes that follow bubbles. For example, Danthine [2] used capital buffers to mitigate systemic risk and Sornette [12] developed a method for detecting bubbles and predicting crashes. In our bubble-taming strategy, we use artificial intelligence, credit scoring, bubble detection and loan adjustments. We verified in our cases that if a bank uses our strategy, it can prevent the bubble from bursting.

2 Model

2.1 Simulation Model

We develop credit scoring and implement it in the simulation to tame the bubble.

2.2 Credit Scoring

In economics, investor status $s(t)$ is defined by using his working capital $w(t)$ as follows:

$$s(t) = \begin{cases} \text{bankrupt}, & \text{if } (w(t) \leq 0) \\ \text{surviving}, & \text{if } (0 < w(t) < 1.4w(t-22)) \\ \text{profitable}, & \text{if } (w(t) \geq 1.4w(t-22)), \end{cases}$$

where working capital is defined by

$$w(t) = \text{cash}(t) + \text{price}(t) \times \text{shares}(t) \text{ - debt}(t), \qquad t\text{: time.}$$

We want to predict this status using artificial intelligence which is one of discriminant analysis, resilient propagation neural network, C4.5 decision tree and support vector machine. The AI works as a function $f(v)$ of eight arguments, which returns probability of investor status:

$$Y \;=\; (y_1, y_2, y_3) = f(v_1, \ldots, v_8), \qquad -1 \leq y_i \leq 1 \; (i = 1,2,3)$$

where the arguments are financial ratios as follows:

1. (market value) / (total assets) = v_1
2. (profit or loss) / (total assets) = v_2
3. (liabilities) / (working capital) = v_3
4. (cash) / (working capital) = v_4
5. (market value) / (working capital) = v_5
6. (profit or loss) / (working capital) = v_6
7. (liabilities) / (total assets) = v_7
8. (cash) / (total assets) = v_8

Each output $(y_i+1)/2,\ (i=1,2,3)$ can be regarded as the probability of investor status. Function $g(Y)$ transforms probability values to corresponding investor status which is one of bankrupt, surviving and profitable.

$$g(Y) = \begin{cases} \text{bankrupt}, & \text{if } (y_1 = \max Y) \\ \text{surviving}, & \text{if } (y_2 = \max Y) \\ \text{profitable}, & \text{if } (y_3 = \max Y). \end{cases}$$

To train the AI, we use the following historical data:

1. Bankrupt: 8 variables one week (5 days) before bankrupt
2. Profitable: 8 variables one month (22 days) before profitable
3. Surviving: 8 variables of surviving data

Our credit scoring accuracy shows that four methods we use have slightly difference results. MDA is 81.94%, C4.5 is 82.27%, RPNN is 81.97% and SVM is 82.023%.

2.3 Taming the Bubble

We develop a new bank strategy to prevent the collapsing price by using credit scoring with artificial intelligence, bubble detection and loan adjustment.

2.3.1 Bubble detection

By simplifying Sornette's method for bubble detection that using log power series, we identify the bubble phenomena with $B(t_i) \geq 2$, where

$$B(t_i) = \frac{EMA(t_i, n)}{EMA(t_{i-5}, n)}, \qquad t_i: \text{ noon of } i\text{-th day}, \;\; n = 5 \text{ (days in one week)}$$

Here $EMA(t_i, n)$ is exponential moving average for n days and is calculated by

$$EMA(t_i, n) = \alpha R(t_i) + (1-\alpha) EMA(t_{i-1}, n), \;\; \alpha = 2/(n+1), \;\; n = 5 \text{ (one week)}.$$

We also compute daily logarithmic return $R(t_i)$ as follows:

$$R(t_i) = \log S(t_i) - \log S(t_{i-1}).$$

2.3.2 Loan adjustment

Loan adjustment is calculated by

$$\text{approved loan} = \text{financing frame} \times \text{proposed loan}.$$

A financing frame is a measure of how much leverage an investor can have from their loan proposal. It is computed by

$$\text{financing frame} = \begin{cases} 1, & (RM(t) \geq 0.7) \\ 0, & (RM(t) \leq 0.1) \\ \frac{10}{6}(RM(t) - 0.1), & (\text{otherwise}) \end{cases}$$

where

$$RM(t) = \frac{\text{(reserve money)}}{\text{(total loans)}}.$$

When the bubble is detected, that is $B(t_i) \geq 2$, the financing frame equation is replaced by the following function:

$$\text{financing frame} = \begin{cases} 1, & (\, g(f(v)) = y_3) \\ \frac{1}{2}(y_2 - y_1), & (\, g(f(v)) = y_2 \geq y_1 \geq y_3) \\ 1 - \frac{1}{2}(y_2 - y_3), & (\, g(f(v)) = y_2 \geq y_3 > y_1) \\ 0, & (\, g(f(v)) = y_1 \,) \end{cases}$$

Here $f(v) = (y_1, y_2, y_3), \qquad -1 \leq y_i \leq 1 \; (i = 1, 2, 3).$

3 The Results

We test a smart bank and a non-smart bank under both static and dynamic reserve money condition. A smart bank is one that has already been trained and a non-smart bank is one that is untrained. Static reserve is the resource that maintain a constant monetary value. A bank's static reserve depends on the total credit extended to all investors. Dynamic reserve is resource which depends on the total market value, which is total number of investor's shares $\times$ the market price.

We consider these both reserve money condition because both systems exist or existed in the real world. At one time, money value was supported by gold reserve and the money was limited so the reserve was static. Today, money value is determined by central bank's balance sheet condition which is consist of loan as asset and deposit as liability. Increasing asset means the bank has delivered more money in the market which is printing new money. It is called money creation. The reserve money now can change dynamically.

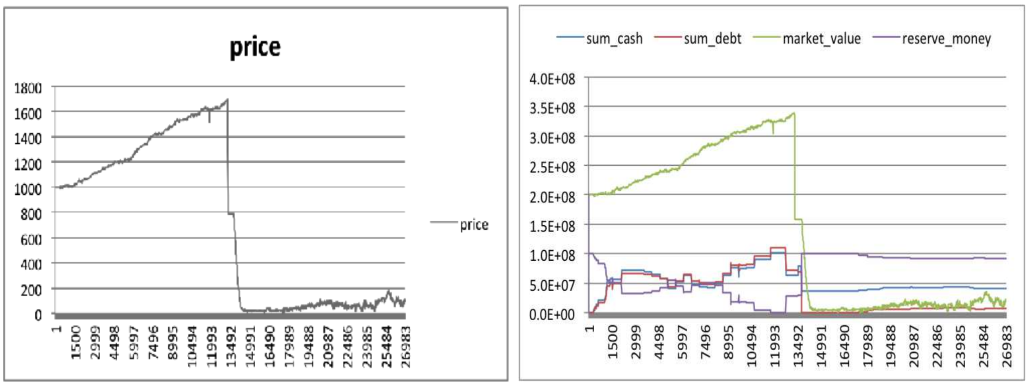
3.1 Static Reserve

A non-smart bank with a static reserve strategy will cause a price collapse because the non-smart bank cannot predict investor status so the bank is unable to request early payment to bankrupt investor. If one big AI investor is bankrupt, he will lead the price to burst. Limiting the amount of cash by static reserve will also have a tendency to cause a collapse. When the reserve is gone, the bank is in a dangerous default condition.

A smart bank can prevent the collapsing price with static reserve. When the reserve is limited, the loans will be restricted. Thus, the prices will decrease slightly. After the reserve is refilled by credit repayments, the bank can relax the loans and the prices will increase. This runs in a continuous cycle. When the bank has large cash deposits, the prices increase steadily. When the bubble is detected, bank also restrict the loan. After bubble condition is disappear bank can relax the loan. The bank maintains market liquidity by assessing the credit scores of investors.

3.2 Dynamic Reserve

When the reserve is unlimited, it depends on the total value of the stock market. It is called the money creation. Dynamic reserve provides unlimited money and generates money creation. It nurtures the price increasing to the new level. The



(a) Non-smart Bank Price Movement (b) Non-smart Bank Reserve Condition

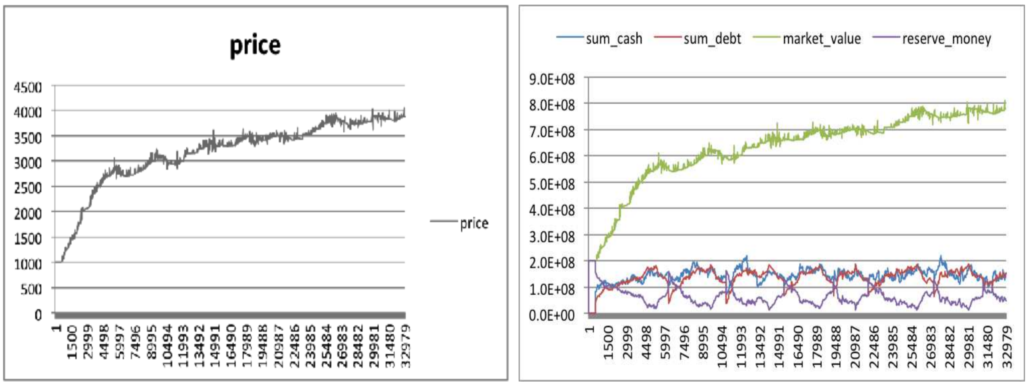
Figure 1: Price Movement and Reserve Condition Non-Smart Bank with Static Reserve

non-smart bank is again unable to prevent the price from collapsing. As bank is unable to predict investor status, the non-smart bank provides loan to any applicant. Thus, when one big AI investor bankrupt, the price movement is collapsing. Severer impact threats the market as price escalating higher with dynamic reserve.

The smart bank can prevent the bursting price although the reserve is unlimited. Increasing price with smart bank is grounded from good investor financial status. Ability to detect the bubble and predict investor status make smart bank is able to deliver the loan to profitable and good surviving investor on the right time. Loan will be restricted if investor status is bad or bubble detection occurs. When condition is safe, bank can relax the loans so market liquidity increases and the price also increases again. Price will move to the new level if investor has good financial status to support it. Thus, smart bank can control money creation to nurture financial development.

4 Conclusion

We have developed a new method for filtering credit requests. The accuracies of the predictions are above 80% and thus our method for credit scoring for margin trading can be used to manage and quantify risk. We also implemented credit scoring in our simulation program. The results of the experiments show that credit scoring can prevent the market crashes by allowing good investors to maintain credit absorption. The financing frame can be adjusted to slow the rate of price in-



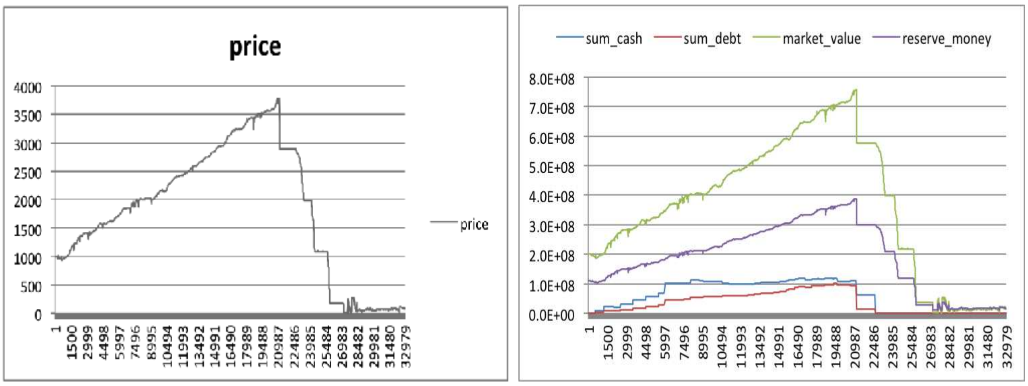
(a) Smart Bank Price Movement (b) Smart Bank with Reserve Condition

Figure 2: Price Movement and Reserve Condition of Smart Bank with Static Reserve

creases, since it can be used to detect bubbles and to monitor the bank's reserves. In general, prices rise when there is growing demand and they drop when there is excess supply. Restricting the entire market heightens the effect of a crash, since the market needs capital in order to maintain the price. In this study, we investigated four methods for creating a credit score; one of these methods was from statistics (discriminant method) and the other three were from the field of artificial intelligence. The accuracy of the artificial intelligence methods was better than that of the statistical method, but the statistical method gave more logical reasons for approving loans.

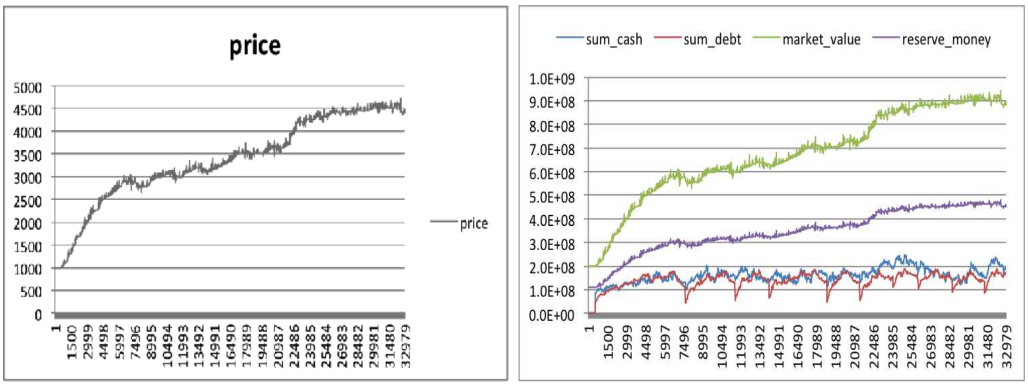
We have created a new strategy that banks can use to tame price bubbles. We investigated several strategies for managing reserves and we investigated how each of them influenced price movement. We found that a smart bank with a dynamic reserve policy can prevent a price collapse and maintain market liquidity.

Future research should aim at improving the accuracy of predicting good investors and quantifying the risk of bankrupt investors. Risk management by hedging potential defaulted loans is another potential area of study.



(a) Non-smart Bank Price Movement (b) Non-smart Bank Reserve Condition

Figure 3: Price Movement and Reserve Condition of Non-Smart Bank with Dynamic Reserve



(a) Smart Bank Price Movement (b) Smart Bank Reserve Condition

Figure 4: Price Movement and Reserve Condition of Smart Bank with Dynamic Reserve

References

[1] E. I. Altman, Financial ratios, discriminant analysis and the prediction of corporate bankruptcy, The Journal of Finance **23-4** (1968), 589–609.

[2] J. P. Danthine, Taming the Financial Cycle, Swiss National Bank, 2012.

[3] S. Finlay, *Credit Scoring, Response Modelling and Insurance Rating*, Palgrave Macmillan, 2010.

[4] E. Gately, *Neural Networks for Financial Forecasting: Top Techniques for Designing and Applying the Latest Trading Systems*, John Wiley & Sons, 1996.

[5] J. Jayanthi, K. S. Joseph and J. Vaishnavi, Bankruptcy prediction using svm and hybrid svm survey, International Journal of Computer Applications **34-7** (2011).

[6] W. Miller, Comparing Models of Corporate Bankruptcy Prediction: Distance to Default vs. Z-Score, Available at SSRN: http://ssrn.com/abstract=1461704 or http://dx.doi.org/10.2139/ssrn.1461704 (2009).

[7] D. Nakatani, Search of Mathematical reduction and optimal investment behavior of the stock market by the simulation, Master Thesis, Kanazawa University, 2010. (in Japanese)

[8] K. Ohara, S. Omata and K. Kobayashi, Private Communications, 2011.

[9] K. Ohara, S. Omata and D. Nakatani, Short selling on virtual stock market, The Proceedings of The 59th National Congress of Theoretical and Applied Mechanics, 281–282, 2010. (in Japanese)

[10] D. L. Olson, D. Delen and Y. Meng, Comparative analysis of data mining methods for bankruptcy prediction, Decision Support Systems **52-2** (2012), 464–473.

[11] N. Siddiqi, *Credit Risk Scorecards: developing and implementing intelligent credit scoring*, John Wiley & Sons, 2006.

[12] D. Sornette and A. Johansen, Significance of log-periodic precursors to financial crashes, Quantitative Finance **1-4** (2001), 452–471.

[13] S. Wang, Measuring Credit Risk for Securities Margin Trading and Securities Lending, International Journal of Innovative Management, Information & Production **4-2** (2013), 7-16.

[14] L. Yu, S. Wang, K. K. Lai and L. Zhou, *Bio-inspired Credit Risk Analysis: computational intelligence with support vector machines*, Springer, 2008.

[15] Zhu Dandan, Short selling of shares using the neural network simulation, Master Thesis, Kanazawa University, 2012. (in Japanese)

平成 27 年　8 月　7 日

学位論文審査報告書（甲）

1．学位論文題目（外国語の場合は和訳を付けること。）

Bank Lending Strategy in The Stock Market

(株式市場における銀行貸出戦略)

2．論文提出者　(1) 所　　属　数物科学　　専攻

(2) 氏（ふり）　名（がな）　Tristiyanto（とりすていやんと）

3．審査結果の要旨（600～650 字）

Tristiyanto 君は、インドネシア政府奨学金給付生として 2012 年 10 月に自然科学研究科数物科学専攻に入学し、株式市場シミュレーションの研究に取り組んできた。現実の株式市場では取引によって価格が決定する。そこで複数の投資家プログラム(人工知能)が取引を実際に行うような株式市場シミュレーションを行うことにした。同君は一種類の株式を扱う単一の株式市場が存在する場合に限定し、信用取引に対する銀行の貸出戦略について研究を行なった。銀行は投資家の将来のクレジットスコアを予想して貸出判断をすることとし、人工知能による予想法を４通り開発し(統計的方法、ニューラルネットワーク、決定木、SVM)、それぞれを比較した。次に十分な株式が流通し、また投資家が資金を調達しやすい状況を考察した。この場合バブル的な現象が発生することとなる。このとき銀行の貸出戦略によっては株価暴落が発生することがあり、投資家の破産により銀行自身も損害を被ることとなる。したがってバブル的な状況を検知したときに銀行が貸出戦略を細かく調整することによって暴落を回避できれば好ましい。同君はその方法を開発し、十分に銀行人工知能を学習させることにより、シミュレータ上では実際に回避できることを明らかにした。同君はこの結果を原著論文１本にまとめた。以上により本論文は、博士（理学）を授与するに値すると判断した。

4．審査結果　(1) 判　　定（いずれかに○印）　合　格　・　不合格

(2) 授与学位　博　士（　理学　）