Fragility Prediction in Banking Sector, An Ordered Probit Model

Roohollah Mohammadi[1] Mahshid Sherafati[2] Bijan Bidabad[3]

Abstract

Over the past two decades, financial crises in banking system have affected many of banks and credit institutes and consequently, many of them have been bankrupt. In this paper, we are going to build index-based model to evaluate the prediction of banking bankruptcy. Two fragility indices were introduced and by using ordered probit model, we estimated the effects of different financial and real sector variables for Iran banking sector. The results demonstrated that exports, short-term debts, and inflation rate have positive impacts, and imports and real official exchange rate have negative effects on the two fragility indices and influence of real official exchange rate on fragility indices was not statistically significant.

Keywords: Financial Crisis, Fragility, Banking, Bankruptcy, Ordered Probit

Introduction

Occurrence of important bankruptcies during 1960s led to a growing interest in the field of bankruptcy predicting models. Global economy has become conscious on the risk in the firms' capital structure, especially after the bankruptcies of large organizations such as WorldCom and Enron. The heavy social and economic costs that bankrupt companies and organizations impose on their shareholders have provoked researchers to propose various methodologies for predicting bankruptcy (Etemadi and Farajzadeh-Dehkordi, 2008).

Bankruptcy always affects a many people in organizations and the society and is difficult to determine the influenced groups because of bankruptcy. It can be claimed that the groups of management, investors, debtors, competitors, and legal entities are more influenced from the bankruptcy than the others. The subject has attracted the attention of researchers due to its critical economic, social, and political consequences that imposes on different groups in the society (Etemadi, Farajzadeh-Dehkordi, 2008).

Financial fragility means high impression of a financial system from small shocks and it may lead a crisis to begin. As a result, identifying the sources of the crisis for making necessary decisions to reduce the severity of its effects is crucial. Crisis in financial system may cause depositors to withdraw their savings from banks, so if depositors expect uncertainty and instability in banking system, they would find a better way to maintain their money and attempt to withdraw their deposits from banks. In addition, since the banks have granted a great portion of customers' deposits as loans, if the loans were not repaid on time, they will be challenged with a sudden decline in their resources and in pessimistic situations, it may even lead to bank bankruptcy (Heydari et al, 2011). In general, it can be said that the financial crisis is defined as a shock or a sudden and rapid change in all or most financial indicators, including short-term interest rates, assets' prices, change in managerial behaviors and performances. The fact that whether small financial perturbations would lead to a financial crisis or not, depends on many factors. The fragility of bank credit growth, reversal rate of expectations, crumble of public trust (such as failure of a financial

[1] CEO of Novin Pajoohan Research Institute, Tehran, Iran. rmohamadi58@gmail.com
[2] MBA Department, Management Faculty, Multimedia University, Malaysia. mahshidsherafati@yahoo.com
[3] Professor of Economics and Chief Economic Advisor to Bank Melli Iran. http://www.bidabad.com bijan@bidabad.com

institution), etc. are all involved in crisis formation (Filosa, 2009). From macroeconomic perspective, economic progress of the society has a consistent and appropriate relationship with the amount of investments. If investment is not formed in favorable opportunities or used inefficiently, national economy will hurt (Mousavi, 2006).

Rapid advances in technology and broad environmental changes and increased competition among economic firms and banks increase the probability of bankruptcy. Bankruptcy and financial crises in banks are not detached from financial and economic crises. Investors, owners, managers, creditors, and government agencies are interested to assess the financial condition of banks; because in bankruptcy, large amounts of costs are imposed on them. Thus, financial decision-making becomes more vital than before. One of the ways to assist investors is to provide them with the predicting patterns on the overall prospects of banks and corporations. The closer the forecasts to reality are, the more correct the bases of their decisions will be (Mehrani et al., 2005).

The bankruptcy probability is a permanent risk for the organizations and companies that work in competitive economic conditions. Managers always seek to have critical information to control this risk. This has caused to found a specialized branch of financial research to respond to the information needs of managers, which focuses on the problem of bankruptcy and its prediction. Moreover, the rapid advances in technology and vast changes in the environment have granted increasing acceleration of economy.

In this paper, we try to predict fragility in banking sector, through ordered probit model.

Background

Given the importance of predicting financial distress and bankruptcy, many researches have been done in the field. Each of these models has the ability of predicting bankruptcy of companies with a percentage of confidence. The preliminary research conducted in the case of bankruptcy prediction was done by Charles Merwin in 1942, who presented a model with three variables of working capital to total assets, net value to total debts, and the current ratio (Raei and Fallah-Pour, 2008). Fu Chen explored the fragility indicator of Estonian banks. Based on the obtained results, market indices are almost useful in predicting financial future fragility and ranking transition economies. He concludes that banking reform is one of the most important elements of economic transformation in the central and Eastern Europe. Michael and Svatopluk (2011) tried to give an index for predicting bankruptcy in the banking sector based on probit model. Using liabilities relative indexes, Čihák (2007) tried to develop financial health indices. By studying the experiences of other developing countries, several factors have shown that might create fragility for the financial system. These variables are imbalanced foreign exchange rate, illogical relationship between offering and receiving loans in accordance with interest rate, their incompatibility with investments' returns, other countries' impacts on capital market, price bubbles due to the unrealistic rolling of demand drifts, inefficiency of rules and regulations, and also lack of establishment of appropriate corporate governance system along with the unstructured banking system.

In this paper, the bankruptcy indicator of the banking sector has been reviewed from January 1999 to December 2010. The bankruptcy of the banking sector is primarily divided into four different periods: the accumulation of risk, stability and the periods of moderate and high bankruptcy. Then, the duration of each level of fragility is identified and in the second step. The purpose of this research is to evaluate some variables for prediction and provide an early warning system for the banks' bankruptcy period. The results demonstrated that there is a significant relationship between stability of banking sector and descriptive statistical values. This study has been conducted by reviewing more than 150 reports of financial stability and plans, which included financial detailed indices in the projects of International Monetary Fund and the Central Bank of Europe. Detailed indices to assess the stability of the banking sector were also discussed.

Wallace (2006) by designing a neural network model, used key financial ratios to explain bankruptcy, which were reported as the best ratios in past bankruptcy studies. The used ratios are working capital to total assets, cash flows to total assets, net profit to total assets, total debts to total assets, current assets to current liabilities, quick assets to current liabilities. The Wallace's model had an overall accuracy of 94 percent. He also reviewed 65 different financial ratios of past studies. Yan Tam and Kiang (1992) also forecast the fragility of banks through neural network model. Neural network model is a competitive method among the existing methods for assessment of the probability of bank bankruptcies. In addition, advantage of neural networks approach over the other methods is that it does not need to apply certain statistical assumptions about the variables' behavior such as assumptions about their probability distribution function or the presumptions on the relations among variables.

Min et al (2006) designed a model for predicting bankruptcy of firms using support vector machine. The research results showed that support vector machine model has better performance to predict firm's bankruptcy than traditional statistical models.

Firouzian et al (2011) used genetic algorithm in predicting bankruptcy and compared it with Altman's Z model for 84 companies in Tehran Stock Exchange. They conclude that genetic algorithm model possesses more accuracy in predicting fragility. Ibrahimi-Kordlar and Arabi (2011) study the application of bankruptcy predicting models (Altman, Falmer, Springit, Zimski and Shirata) in predicting default of the loans granted to Tehran Stock Exchange companies by Bank Sepah. It was realized that blocking resources because of due and deferred demands may reduce the banks' capability to provide credit loans and consequently, can have a negative effect on productivity. Correct and precise decisions at the times of granting loan are one of the most important ways to prevent overdue demands. The most important tools include validation and credit ranking of customers. According to the findings of this study, Altman and Springit models have been identified as suitable for customers' credit ranking system. The results of studying the predicting power of these models indicate that there is a significant difference between the results of these models. Additionally, Altman and Springit models have the greatest potential for prediction. Bahrami (2010) by giving an overview of bankruptcy models examines the accuracy of Altman model in Tehran Stock Exchange companies. This study tries to answer the question that which model for predicting bankruptcy fits better to the specific conditions of Tehran Stock Exchange companies. It also reviews the accuracy percentage of Altman model in such economic conditions in the selected companies during 2001-2007. Using applied-descriptive statistics, the results show that, despite the fact that Altman model is a traditional model, it still possesses more accuracy to explain bankruptcy.

Empirical Investigations

We used ordered probit model to predict the fragility of banks during 2003-2011 in Iran. Ordered probit is an extension of probit model to the case that there are more than two outcomes for an ordinal dependent variable. The model was estimated after collecting data using Eviews software. Dependent variable is Banking Sector Fragility Index (BSFI), which has been suggested by Kibritciouglu (2002). This index is used as arithmetic mean of four variables of banking sector and represents three main risks of credit risk, liquidity risk and exchange rate risk. The four variables of this index include:

CPS: Annual percentage change of non-government loans, as index of credit risk
FL: Annual percentage change of the bank foreign liabilities, as index of exchange rate risk
DEP: Annual percentage change of real bank deposits, as index of liquidity risk
RES: Annual percentage change of foreign exchange reserves in the banking sector

BSFI offers an appropriate base to recognize the values of fragility period and is calculated as:

$$BSFI_t = \frac{\left(\frac{CPS_t - \mu_{cps}}{\sigma_{cps}}\right) + \left(\frac{FL_t - \mu_{ft}}{\sigma_{ft}}\right) + \left(\frac{DEP_t - \mu_{dep}}{\sigma_{dep}}\right) + \left(\frac{RES_t - \mu_{res}}{\sigma_{res}}\right)}{4}$$

$$CPS_t = \frac{LCPS_t - LCPS_{t-12}}{LCPS_{t-12}}$$

$$FL_t = \frac{LFL_t - LFL_{t-12}}{LFL_{t-12}}$$

$$DEP_t = \frac{LDEP_t - LDEP_{t-12}}{LDEP_{t-12}}$$

$$RES_t = \frac{LRES_t - LRES_{t-12}}{LRES_{t-12}}$$

Where

t: Time (beginning of the year)

t-12: Time (end of the year)

μ: Arithmetic mean of the related variables

σ_{cps}: Standard deviation of annual percentage change of non-government loans

σ_{ft}: Standard deviation of annual percentage change of bank foreign liabilities

σ_{dep}: Standard deviation of annual percentage change of bank deposits

σ_{cps}: Standard deviation of annual percentage change of bank foreign exchange reserves

Independent variables of the model include exports, imports, inflation rate, short-term debts, and the real official exchange rate. Export variable (million dollars) is exported goods excluding exports of oil and gas products and import variable (million dollars) were derived from Iran Customs Administration (IRICA). Official exchange rate is conversed by Central Bank. Short-term debts refer to that part of foreign obligations (million dollars) that their payment due date is less than one year. Real official exchange rate was calculated as multiplication official exchange rate (Rials/dollar) by foreign (USA) consumer price index and divided by domestic consumer price index. Statistical population of the research includes all commercial banks of Iran. We estimated descriptive statistics, which were resulted from the ordered probit model as are shown by the table 1.

Table 1 – Descriptive statistics of research variables

Variable	Mean	Standard deviation	Minimum	Maximum
Exports	16933.19	8729.43	5960.2	33818
Imports	47648.51	12113.91	26585.8	64363
Real official exchange rate	59840.03	1491.03	8382.6	3868
Short term debts	8602.47	2693.28	2065.2	11612
Inflation rate	0.147	0.006	0.02	0.253

Source: Software output

Table 2 – Descriptive statistics of banking variables (2003-2011)

Variable	Mean	Standard deviation
Annual percentage change of non-government loans (CPS)	27.83	63.92
Annual percentage change of the bank foreign liabilities (FL)	19.98	29.61
Annual percentage change of bank deposits (DEP)	19.02	17.51
Annual percentage change of foreign exchange reserves (RES)	14.63	27.61

Source: Software output

The fragility index was calculated as the arithmetic mean of four variables of the banking sector, including the annual percentage change of non-government loans in private sector, annual percentage change of bank deposits, annual percentage change of bank foreign liabilities, and annual percentage change of foreign exchange reserves. Results of the descriptive statistics are listed in table 2.

The correlation between the calculated indices of $BSFI_3$ and the variables of annual percentage change of non-government loans in private sector, annual percentage change of bank deposits, and annual percentage change of the bank foreign liabilities are shown in Table 3. Pearson's correlation between $BSFI_4$ index and the mentioned variables and annual percentage change of the bank foreign exchange reserves are presented by Table 4.

Table 3 – Matrix of Pearson's correlation between $BSFI_3$ index and related variables

	$BSFI_3$ index	Annual percentage change of non-government loans	Annual percentage change of the bank foreign liabilities	Annual percentage change of bank deposits
$BSFI_3$ index	1			
Annual percentage change of non-government loans	0.50	1		
Annual percentage change of the bank foreign liabilities	0.31*	0.63*	1	
Annual percentage change of bank deposits	- 0.03	- 0.09	- 0.208*	1

Source: Software output

Table 4 – Matrix of Pearson's correlation between $BSFI_4$ index and related variables

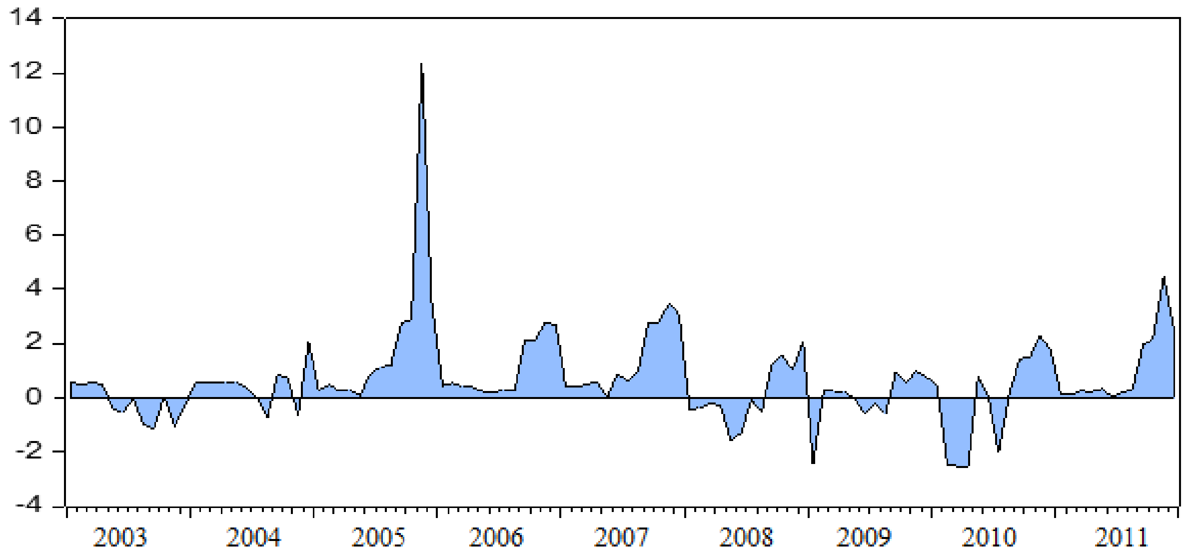
	$BSFI_4$ index	Annual percentage change of non-government loans	Annual percentage change of the bank foreign liabilities	Annual percentage change of bank deposits	Annual percentage change of the bank foreign exchange reserves
$BSFI_3$ index	1				
Annual percentage change of non-government loans	0.51*	1			
Annual percentage change of the bank foreign liabilities	0.31*	0.63*	1		
Annual percentage change of bank deposits	0.69*	0.57*	0.63*	1	
Annual percentage change of the bank foreign exchange reserves	- 0.03	- 0.09	0.19*	0.09	1

Source: Software output

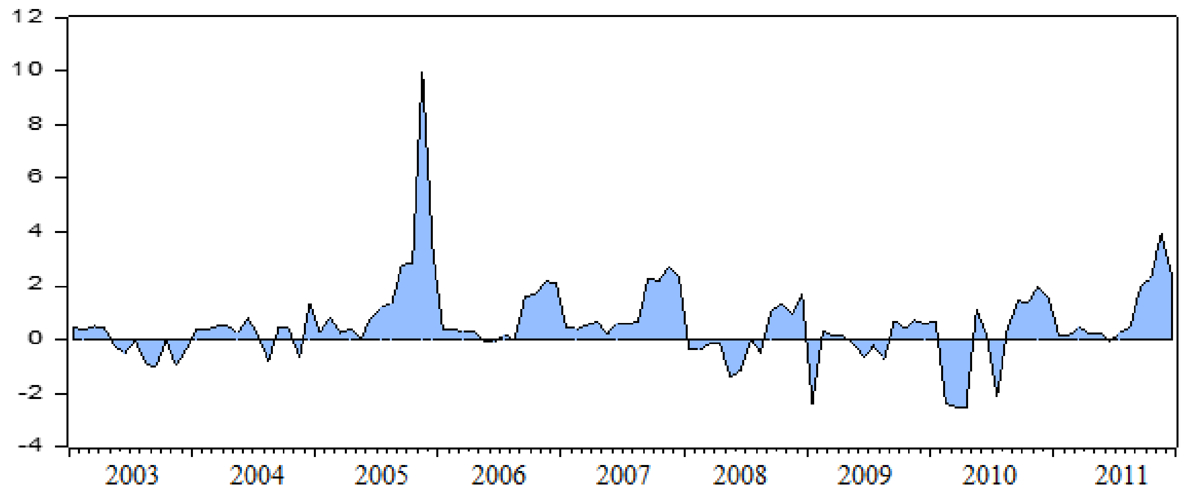
The results of Pearson's correlation coefficients show that there is a significant and positive relationship between the $BSFI_3$ index and annual percentage change of non-government loans in the private sector and the annual percentage change of the bank foreign liabilities. Annual percentage change of loans and foreign debts have a strong positive effect on the value of $BSFI_3$ index. There is an insignificant negative relationship between this index and the annual percentage change of bank deposits.

The results of Pearson's correlation coefficients show that there is a significant positive relationship between the $BSFI_4$ index and annual percentage change of non-government loans in the private sector, annual percentage change of bank foreign liabilities, and annual percentage change of bank deposits. This indicates that the annual percentage change of loans, liabilities, and deposits have strong positive effects on $BSFI_4$ index, and there is an insignificant negative relationship between this index and annual percentage change of the bank foreign exchange reserves. Time charts of fragility indices of $BSFI_3$ and $BSFI_4$ for the period 2003-2011 are shown in following figures:

BSFI3



BSFI4



As expected before, by comparing the time charts of the two fragility indices, it was revealed that fragility index $BSFI_4$ has more stability and constancy than $BSFI_3$ index during the study period. Fragility index is categorized into three periods of high fragility, medium fragility, and risk as shown by table 5. The months listed in this table include the fragility periods and the blank cells present stability.

Table 5 – Fragility periods according to BSFI index

Standard deviation 1.71 ($BSFI_3$)			Standard deviation 1.47 ($BSFI_4$)		
High fragility	Medium fragility	Risk	High fragility	Medium fragility	Risk
	Jul-Aug 2003			Jul-Dec 2003	
	Jan-Feb 2004			Oct 2004	
	Oct 2004			Jan 2005	
	Jan 2005	Feb 2005			Nov 2005-Feb 2006
		Nov 2005-Feb 2006		Jul-Aug 2006	
		Nov 2006-Feb 2007		Oct 2006	Jan-Feb 2007
		Nov 2007-Feb 2008			Nov 2007-Feb 2008
	Mar-Oct 2008	Feb 2009			Feb 2009
	Mar 2009		Mar 2009	Jul-Oct 2009	
	Jul-Oct 2009		Apr-Jun 2010	Sep 2010	Jan-Feb 2011
Apr-Jun 2010				Aug 2011	Nov 2011-Jan 2012
Sep 2010		Dec 2010-Feb 2011			
		Nov 2011-Feb 2012			

In general, the areas under the two curves for the two fragility indices of $BSFI_3$ and $BSFI_4$ in these figures show the progression of the bank fragility during the period of stability. By examining the trend of indices in both figures according to the standard deviation values in three states of high fragility, medium fragility, and risk, it can be perceived that the period of Nov 2005 - Feb 2006, which includes the risk period, indicates the probability of crisis in the future of banking sector. Given the fact that this period was short, it can be concluded that the bank policies and activities have acted well in preventing the crisis. After a short period, the circumstances are improved. Then, a one-month risk can be observed in Jan-Feb 2007 in the banking sector. Therefore, the peak of fragility index trend is less than the previous risk period. Unfortunately, the fragility index trend in the beginning of the years 2007, 2008, 2010, and 2011 represent short periods of risk. These periods, as the starting points of crisis, serve as risky points for the banking sector, because if the collapse of index is not controlled, the banking sector will enter into the fragility trend (medium and high). The index trend less than the standard deviation indicates medium and high fragility. As can be witnessed, in short periods in 2009 and 2011, medium fragility, and in short periods in 2009 and 2010, high fragility are observable.

Probit Model for $BFSI_4$

In the ordered probit, dependent variable is a tetragonal variable and our independent variables are exports, imports, inflation rate, the government's short-term debts, and exchange rate.

Table 6 – Coefficients of the model's predicting variables and their significance results

Independent variable	Coefficients	Standard deviation	Z statistics	P-Value	Test results
Exports	$8.43*10^{-5}$	$4.01*10^{-5}$	2.11	0.03	Significant
Short term debts	0.00279	$6.09*10^{-5}$	4.58	0.000	Significant
Imports	- 0.00016	$4.81*10^{-5}$	- 3.22	0.001	Significant
Inflation rate	0.00643	2.08	3.08	0.002	Significant
Real official exchange rate	- 0.0006	0.0004	- 1.58	0.111	Insignificant

Other statistics

AIC Statistics	2.146
R^2	0.8055
LR Statistics	25.46
P-value	0.000113

The results obtained from the test of model coefficients show that at 95% confidence level, coefficients of variables of exports, imports, short-term debts, and inflation rate are significant and only the variable of real official exchange rate is insignificant. The low value of Akaike Information Criterion (AIC), the high value of the coefficient of determination (R^2), and the significance of Likelihood Ratio (LR) statistics (with the P- value of smaller than 0.05) also confirm the results of the model fitness. Thus, it can be expressed that the defined model in terms of $BSFI_4$ index is appropriate to achieve the prediction for Early Warning System (EWS) in Iran banking environment.

The estimated coefficients from the probit model based on $BSFI_4$ index present that for a million dollar increase in exports, fragility will probably increase very little, i.e. 8.43×10^{-5} units. For a million dollar increase in imports, fragility will probably decrease by 0.00016 units. For a million dollar increase in government's short-term debts, fragility will probably increase by 0.00279 units. For a unit increase in inflation rate, fragility will probably increase by 0.00643 units. And, for a unit increase in real official exchange rate, fragility will probably decrease by 0.0006 units.

Probit Model for $BFSI_3$

The results of estimating the ordered probit model for $BSFI_3$ index are shown by table 7. The results from the test of model coefficients showed that at 95% confidence level, coefficients of variables of exports, imports, short-term debts, inflation rate, and real official exchange rate are significant. The low value of Akaike Information Criterion (AIC), the high value of the coefficient of determination (R^2), and significance of Likelihood Ratio (LR) statistics (with the P- value of smaller than 0.05) verify the results of the model fitness. Accordingly, it can be claimed that the defined model is appropriate in terms of $BSFI_3$ index, in order to achieve the prediction for Early Warning System (EWS) in Iran banking sector.

Table 7 – Coefficients of the model's predicting variables and their significance results

Independent variable	Coefficients	Standard deviation	Z statistics	P-Value	Test results
Exports	0.000117	$4.17*10^{-5}$	2.79	0.000	Significant
Short term debts	0.0035	$6.72*10^{-5}$	3.513	0.0004	Significant
Imports	- 0.00224	$5.24*10^{-5}$	- 4.28	0.024	Significant
Inflation rate	0.00773	2.20	3.51	0.005	Significant
Real official exchange rate	- 0.000935	0.000415	- 2.25	0.000	Significant

Other statistics	
AIC Statistics	1.97
R^2	0.9526
LR Statistics	35.63
P-value	0.000

The estimated coefficients from the probit model based on $BSFI_3$ index show that for a million dollar increase in exports, fragility will probably increase by 0.000117 units. For a million dollar increase in imports, fragility will probably decrease by 0.000222 units. For a million dollar increase in government's short-term debts, fragility will probably increase by 0.0035 units. For a unit increase in inflation rate, fragility will probably increase by 0.007736 units. For a unit increase in real official exchange rate, fragility will probably decrease by 0.000935 units.

Conclusions

Except the relatively constant trend of exports and imports in the period under consideration, other trends, including real official exchange rate, inflation rate, foreign short-term debts in 2010, experienced shock. This shock is the consequence of the subsidy reform plan, which has already affected the banking fragility index. In fact, during recent years, the banking fragility index has increased substantially. This index is a combination of changes in non-government loans, changes in bank's foreign debts, and changes in banking deposits. In other words, irregularities and unorganized plans in the economic system have increased liquidity risk, credit risk, and exchange rate risk in the banking system. In such circumstances, avoiding command-based economy to decrease the interest rate of loans, and maintaining the sovereignty of Central Bank to control liquidity and decreasing inflation can be appropriate solutions to control banking fragility index. Based on the obtained results from the research, inflation rate is one of the most influential factors on the banking fragility. Thus, it is suggested that government takes contractionary policies (such as not initiating the second phase of subsidy reform plan until achieving relative economic stability) in order to control the liquidity level. Short-term debts are the second factor affecting the country banking system fragility. Short-term debts experienced a sudden and considerable increase in 2010. Although it diminished in 2011, it is necessary to control this variable to maintain stability in banking system.

Findings of this paper can be influential in identification and improvement of warning indicators for emergence of crises. Even though the time of crisis is unpredictable, it is likely to monitor the factors leading to financial imbalance such as quick, unexpected, and fast growth of credit and asset prices.

Suggestions for Further Research

We had not access to some variables, such as annual percentage change of non-government loans in the banking sector, bank foreign debts, bank deposits, and the required foreign exchange reserves, for calculation of BSFI index for the years before 2003. Lack of access to general financial report of banking system in Iran for calculation of the variables in a way that separated information for commercial banks, private banks, financial and credit institutes be available and we just focused on commercial banks.

Considering the reciprocal impact of macroeconomic variables on fragility in the banking sector, it is recommended to examine the proposed model of this study by the vector autoregressive model and then, compare the obtained results with the findings of this research. It is also suggested to predict the banking fragility by using heuristic algorithms (such as neural networks, genetic algorithm, imperialist competitive algorithm, etc.).

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