

STUDY ON EARLY WARNING INDICATORS OF BANK RUNS IN INDONESIA: MARKOV-SWITCHING APPROACH

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Abstract

A run on a bank occurs when a large number of depositors, fearing that their bank will be unable to repay their deposits in full and on time, simultaneously try to withdraw their funds immediately. A run on a particular bank can lead to a banking crisis if it spreads to other banks (contagious effect). Bank runs and banking crises have become a global phenomenon and have occurred repeatedly in many countries since the era of modern banking. In the case of Indonesia, bank runs have also reoccurred time and again. In 1992, bank runs affected several national banks, subsequently precipitating the liquidation of one bank. Then in 1997/1998, bank runs developed into the worst banking crisis ever witnessed in the banking history of Indonesia.

Considering the extent of losses attributable to bank runs and the banking crisis, extensive studies on the early warning indicators of bank runs are urgently required to prevent future bank runs and banking crises. This paper aims to comprehensively analyse the early warning indicators of bank runs for all banks in Indonesia, both during the sample period of 1990-2005 as well as during the banking crisis in 1997-1998. The study of early warning indicators of bank runs uses the Markov-Switching model.

To calculate the transition probability from a tranquil state to a state of bank run uses the Markov-Switching process through an auto-regressive approach. The change in deposits held at each bank is used as a variable of bank runs. The results of Markov-Switching (MS) show that the MS model is robust as an early warning indicator of bank runs. This is reflected by testing, which was performed on the actual incident of 102 banks, showing that the MS model only produced false signals an estimated 0.69% - 2.08% of the time.

JEL Classification: C22, G21

Keywords: Bank Runs, Early Warning Indicators, Markov-Switching

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1. Introduction

Bank runs occur as a result of bank fragility to customer withdrawals. Such fragility stems from the business activity of a bank, which transforms short-term liabilities, like checking accounts, savings and term deposits, into longer-term assets, like loans. Accordingly, banks are continuously faced with the problem of a maturity mismatch and are thereby vulnerable to large-scale withdrawals (bank runs) by their customers due to limited customer ownership of liquid assets. A bank run is ostensibly triggered by a loss of public confidence in a bank. This loss of confidence can stem from internal bank factors, like a decline in performance, as well as other factors, like an economic downturn or externalities like contagion.

Empirical experience demonstrates that bank runs can severely undermine the economy of the affected country, in particular if a banking crisis also emerges. Banking crises that develop from bank runs lead to a break in the bank intermediation function, thereby purging the business community of its financing sources. When financing sources dry up it can spell the end for business activity and production and ultimately lead to an economic slowdown or contraction as well as increased unemployment. Fiscally, a banking crisis will exacerbate the cost of recovery to save the affected banks. Furthermore, this cost of recovery is ultimately borne by the taxpayer.

Crisis experience gleaned in Asia during 1997/1998 indicates that it was a banking crisis as one of the primary factors causing countries in the region to suffer a severe economic contraction. The Indonesian economy experienced the deepest contraction, reaching -13.1% in 1998. Meanwhile, the economies of Thailand, Malaysia, South Korea and the Philippines experienced respective contractions in the same year of 10.5%, 7.4%, 6.9% and 0.6%. In addition, the cost of restructuring the banking sector during the crisis reached a whopping 45% of gross domestic product in Indonesia, 15% in Korea and 12% in Malaysia (Lindgren et. all. 1999).

Considering that bank runs can occur time and again and their impact can trigger significant economic losses, an in-depth review of early warning indicators to prevent the occurrence of bank runs is timely and pertinent. In general, this research paper on early warning indicators (EWI) utilises two main models, namely a signal extraction model and an econometrics model.

The signal extraction model uses a non-parametric approach by observing the behaviour of particular variables before and after a crisis. The most commonly cited model used as a reference in the research was developed by Kaminsky (1998, 1999) for early warning indicators of an exchange rate crisis and banking crisis, as well as the model developed by Kaminsky, Lizondo and Reinhart (1998) as an EWI for an exchange rate crisis. Another type of model used to detect banking crises is an econometric model, one of which is the logit model. Demirgüç-Kunt and Detragiache (1998) utilised a logit model to detect banking crises. In the research, the possibility of a crisis was assumed as a function of the explanatory variable vector, with the value of the dependent variable equal to 0 for no crisis and 1 in the event of a crisis.

Several authors have conducted studies on early warning indicators for the financial sector in Indonesia. Research undertaken by Agung et al. (2003) and Dewati et al. (2004) discuss early warning indicators for an exchange rate crisis and financial crisis in Indonesia using the signal approach. This approach contains a number of inherent weaknesses, primarily relating to the arbitrary determination of the crisis threshold value and crisis time frame. Research conducted by Bank Indonesia (2003a , 2003b and 2003c) reviewed an EWI for financial system stability using discriminant analysis and a logistic regression but the research did not cover bank runs. Bank Indonesia (2004a) also studied a bankruptcy prediction model for commercial banks in Indonesia using factor analysis and logistic regression; however bank runs were not mentioned.

Against this rather sparse backdrop, this paper strives to develop early warning indicators to detect the possibility of individual bank runs using the Markov-Switching model. After the Introduction, this paper discusses the theoretical foundations and empirical results of previous research. The subsequent section outlines a picture of national bank performance under crisis conditions and the empirical model used. The fourth part of the paper presents the empirical results followed in the final section with the conclusion and recommendations to prevent further bank runs.

2. Bank Runs and Early Warning Indicators

Numerous early warning indicators (EWI) for individual banks were developed using preliminary empirical reviews in the mid-1970s. Research by Gonzalez-Hermosillo (1999) postulated that the collapse of a bank is caused by liquidity conditions, the market or credit risk. These three factors are certainly affected by the characteristics of an individual bank as well as macroeconomic conditions. In order to capture the impact of different effects, Gonzalez-Hermosillo (1999) developed a regression model using several banking indicators (like a proxy of market risk, credit risk, liquidity risk and moral hazard) in conjunction with macroeconomic and regional variables. The research also explicitly investigates how the collapse of an individual bank can be affected by financial sector vulnerabilities as a whole (for instance, with the consideration of contagion). Specifically, the research includes a ratio of total credit to output as a measure of banking sector vulnerability in a regression.

Congruous with research conducted by the US Federal Deposit Insurance Corporation (FDIC) in its early warning indicator system, Gonzalez-Hermosillo (1999) differentiated between indicators of vulnerability stemming from risk factors that can cause a bank to collapse. In general, an increase in non-performing loans and a drop in the capital adequacy ratio are good indicators of an impending bank collapse. However, only a handful of main indicators of a crisis have been proposed for estimating the collapse of a bank. The most salient points of these researches include growth in property credit and interbank placements as indicators of possible bank default. Conversely, higher credit approval and a growing share of tradable securities lead to a lower possibility of bank collapse. Meanwhile, contagion influences the collapse of a bank in a number of cases but the effect is minor.

Davis and Karim (2007) found that their research on early warning indicators (EWI) required the right approach, among others, using the logit method and signal extraction. The different methods used also produced different performance and crisis prediction indicators. The logit method garnered most support for a global EWI, while signal extraction was found to be more country specific. In line with financial sector liberalisation and development¹, it is imperative to utilise EWI for crisis prevention.

¹ According to Karim dan Davis (2007) financial sector liberalisation is the opening up of financial institutions based on market mechanisms by removing government constraints in the form of regulations.

Demirguc-Kunt and Detragiache (1999) conducted a study to predict the probability of banking crises, intended to be used as an instrument to monitor vulnerabilities in the banking sector. Their research used the multivariate logit method with panel data, and variables that reflect the macroeconomy and financial sector. The macroeconomic variables included: GDP growth, changes in the terms of trade, exchange rate depreciation, inflation and budget surplus/GDP. Meanwhile, the variables chosen to reflect the characteristics of the financial sector were: M2/foreign exchange reserves and the level of bank credit growth with a two-period lag. In addition, GDP per capita was used as a proxy for the structural characteristics of the economy. The results of the study indicated that low GDP growth, high real interest rates, high inflation and strong credit growth in the past as well as the magnitude of the M2 ratio to forex reserves simultaneously trigger a higher incidence of banking crisis. Conversely, exchange rate depreciation, the terms of trade and budget surplus to GDP were not found to be significant.

Utilising probit or logit regression models as well as the signal approach as early warning indicators has a number of weaknesses. First is arbitrarily determining the date of the onset of the crisis, which tends to be late (Von Hagen and Ho, 2003). Second is that early warning banking industry indicators using a correct and minimal standard deviation (noise) to signal have limitations. These limitations necessitate the arbitrary determination of the banking crisis threshold value. Different research papers have used different thresholds without providing any strong arguments for the reason why. Eichengreen, Rose and Wyplosz (1996) set the crisis threshold at 1.5 standard deviations from the mean, while Kaminsky and Reinhart (1999) set the threshold at three standard deviations from the mean. In addition, the crisis threshold also depends heavily on the size of the sample. Additional data or longer periods can alter the crisis threshold. The third weakness is that transforming the crisis index into binary can exclude relevant information.

Due to the weaknesses exposed when using the probit/logit approach and arbitrarily determining the crisis threshold, the Markov-Switching model is preferable when investigating exchange rate crises and banking crises. Utilising this model is not only limited to identifying the crisis period but it can also be used to predict the occurrence of banking crises. The use of Markov-Switching in analysing or detecting the occurrence of banking crises has a number of advantages. **The first advantage** is that the crisis threshold value is an endogenous variable or, in other words, the crisis period and its duration form part of the results to be estimated. Using this

approach, the economy is assumed to be in a tranquil state or crisis state. Therefore, neither of these states can be observed directly and both are latent variables. Nonetheless, indicators of both states can be observed directly by monitoring behaviour in both economic states. The two states are different, with a higher and more fluctuating value for a crisis state when compared to a tranquil state (normal period). The shift in value from one state to the other depends on the transition probability. According to the characteristics of Markov, the value of an upcoming state depends on the current state. Therefore, this model permits the possibility of a crisis state remaining in a state of crisis.

The second advantage is that the Markov-Switching model allows the use of continuous dependent variables. Using changes in deposits or its index can prevent a loss of information if the data is transformed in the form of a dummy variable. **The third advantage** of using this model is that it can capture dynamic information from the crisis. Therefore, this model can be used to estimate the duration of the crisis period from the probability of the transition period. **The fourth advantage** is that this model can be used for non-linear behaviour.

Using Markov-Switching to detect exchange rate and banking crises has developed in recent years due to the weaknesses found in the signal approach, namely arbitrarily determining the crisis threshold. Abiad (2003) used the Markov-Switching approach to analyse an early warning system for exchange rate crises in Asia. Based on this research it was found that the model works well when detecting the occurrence of exchange rate crises in Asia. The model could detect two-thirds of the crisis periods in the sample and created fewer false signals compared to the previous models, namely the signal approach. Research by Alvarez-Plata and Schrooten (2003) and Ho (2004) also produced robust results using this model to detect exchange rate crises respectively in Argentina and Asia.

Meanwhile, Ho (2004) used the Markov-Switching model to detect banking crises utilising aggregate data. The results of this research showed that this model can successfully detect banking crises in Asia. In the case of Indonesia, Agung et. al. (2003) developed an early warning system to predict exchange rate and banking crises by modifying the signal extraction model developed by Kaminsky, Lizondo and Reinhart (1999). The modifications included trying to capture abnormal behaviour from the indicators used, not individually but using aggregate indices. This was undertaken considering that leading up to a crisis such indicators usually move in unison. The variables used include: macroeconomic indicators (real appreciation of the

domestic currency, M2/foreign exchange reserves) to predict exchange rate crises; and aggregate banking micro indicators (net interest margin) to predict banking crises. The results show that the signals produced from this early warning system are relatively satisfactory with respective probabilities of accuracy amounting to 67% and 90%.

3. Bank Performance amid a Crisis

At its outset, the crisis that befell the Indonesian economy in 1997 was triggered by an exchange rate crisis on the rupiah. Intense depreciatory pressures stemmed from contagion from the baht exchange rate crisis happening in Thailand in July 1997. The affect of this contagion not only reached Indonesian shores but also spread quickly to other countries in Asia like the Philippines, Malaysia and South Korea. The government intervened by introducing economic policy packages in September 1997 in order to protect the domestic economy from a deeper crisis as a result of depreciatory pressures and capital outflow. This program was subsequently extended to become an economic stabilisation and reform program, garnering the formal support of the IMF, World Bank and ADB in November 1997. In the implementation of this financial sector reform program to restore the banking system, 16 national private banks were closed on 1st November 1997.

The closure of 16 banks triggered widespread bank runs on those banks deemed unsound by the general public. Consequently, the policy to close banks, which should have saved the national banking industry, actually provoked bank runs on banks not owned by the state. These bank runs occurred due to a collapse of public confidence in the banking industry due to the bank closures. As the bank runs spread the financial performance of all banks began to suffer, with credit losses and lower bank earnings, due to poor managerial practices that did not adhere to aspects of good governance (Warjiyo, 2001 and Bank Indonesia, 1998).² In addition, rapid rupiah depreciation swelled the foreign debt of banks denominated in rupiah, which was exacerbated further by the lack of a guarantee program. The absence of a guarantee program and lack of information regarding the condition of the banks (asymmetric information), forced the banks' customers, especially the customers of private banks, to withdraw their deposits and divert them to banks considered more sound with safer assets (currency).

² 1997/1998 Bank Indonesia Financial Report.

One month after the 16 banks were closed (December 1997), total deposits held by national private commercial banks declined by as much as Rp 22.9 trillion (11.94%). Withdrawals began as soon as the banks were closed and peaked in December 1997 and January 1998. The withdrawals began to ease when the government introduced a blanket guarantee scheme in January 1998. However, when social unrest erupted in May 1998, the number of banks experiencing runs increased again.

Based on monthly bank reports submitted to Bank Indonesia, most bank runs affected non foreign exchange banks³, banks with frozen business activity⁴ and banks with frozen operations.⁵ Runs on non-foreign exchange banks peaked in December 1997, January 1998 and May 1998. As an illustration, in December 1997 of the 45 non foreign exchange banks, 25 experienced up to a 10% decline in deposits, 17 experienced up to a 20% decline, 13 experienced up to a 40% decline, 11 experienced up to a 60% decline and six banks experienced a decline of up to 80% of their total funds compared to the previous month.

Similar to the case of non-foreign exchange banks, runs also affected banks with frozen business activity (BBKU) and banks with frozen operations (BBO). Most withdrawals occurred in November 1997 up to 1998, as well as in March through May 1998. For instance, in November 1998, of the 40 BBKU as many as 26 experienced a decline in deposits of up to 10% compared to the previous month, while 14 banks experienced a decline of up to 20% and two banks experienced a decline in deposits of up to 40%. Bank runs on BBO followed a similar pattern to those on BBKU. In January 1998, of the 10 banks with frozen operations, six experienced up to a 20% decline in deposits on the previous month, while 4 banks experienced a decline of up to 40%.

During the period from November 1997 to January 1998, of the seven state-owned banks none experienced a drop in deposits of up to 10%. In fact the opposite was true, namely that deposits at state-owned banks actually experienced positive growth of 9.6% in November 1997. Similarly, withdrawals from foreign banks followed a similar pattern as those from state-owned banks. In November 1997, only one foreign bank experienced any decline in deposits.

³ Non foreign exchange banks are national private banks that are not permitted to undertake any foreign exchange activity in their business activity.

⁴ Banks with frozen business activity are banks that are temporarily not permitted to undertake any business activity for a given period of time.

⁵ Bank with frozen operations are banks that have had their operational activities temporarily suspended.

Meanwhile, from December 1997 to January 1998 no declines of up to 10% were reported. In actuality, deposits indicated 6.8% growth in November 1997.

Against this backdrop, the share of deposits held at state-owned and foreign banks increased respectively from 42.8% and 7.2% in December 1997 to 47.7% and 9.3% at the end of January 1998. In contrast, the share of deposits held at foreign exchange banks and non-foreign exchange banks contracted from 43.2% and 2.2% in December 1997 to 36.9% and 1.5% in January 1998 respectively (Table 1). This trend demonstrates a shift in funds from private banks to state-owned and foreign banks (flight to quality).

Table 1. Share of Bank Deposits

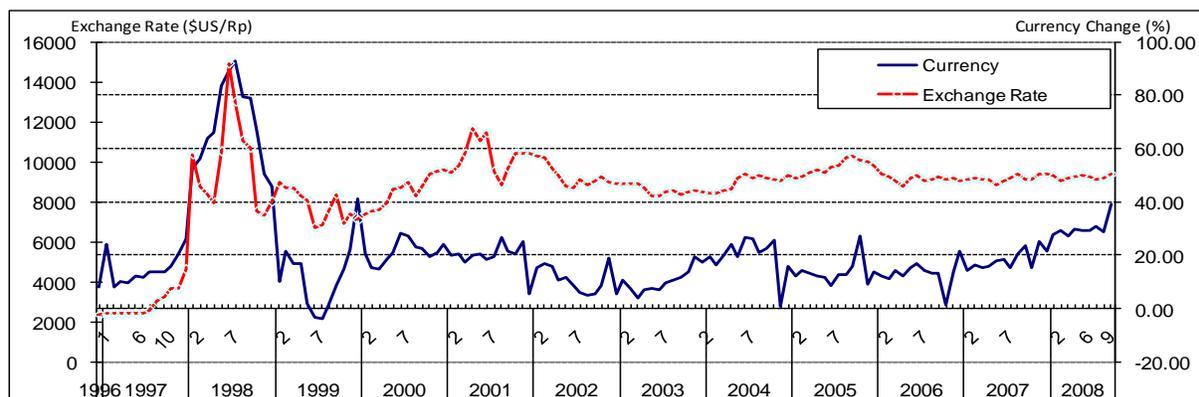
Bank Group	Share (%)				
	Dec. 1996	Dec. 1997	Jan. 1998	Feb. 1998	Mar. 1998
Commerical banks:					
1. Stated-owned banks	36.0	42.8	47.7	47.0	46.6
2. Foreign exchange banks	49.7	43.2	30.9	37.1	37.0
3. Non-foreign exchange banks	5.5	2.2	1.5	1.9	2.3
4. Regional development banks	2.8	2.2	1.6	1.7	1.6
5. Joint-venture banks	1.7	2.4	3.0	3.0	2.8
6. Foreign Banks	4.1	7.2	9.3	9.3	9.2
Rural Banks*)	0.5	0.4	0.3	0.3	0.3

*Share against commercial banks

Source: Bank Indonesia

In addition to widespread flight to quality, funds were also diverted into currency, as reflected by the 31.8% increase in currency in the month of January 1998 (Rp 9.045 trillion) compared to the previous month. This trend does not follow the usual pattern of demand for currency, which based on the two years prior to the crisis averaged just 9.5% annually.

Figure 1. Currency and the Exchange Rate



The banking crisis was further compounded by severe rupiah exchange rate depreciation. In January 1997, the value of the rupiah against the US dollar was Rp 2,396. This position was untenable and the rupiah began to slide. In July 1997, the position of the rupiah against the dollar was Rp 2,599 and in December 1997 it was Rp 4,650. In 1998 the rupiah weakened dramatically to Rp 10,525 per US dollar in May 1998 and continued to deteriorate to its nadir in June 1998 at Rp 14,900. From this low point the rupiah began to recover, reaching Rp 8,025 in December 1998.

Bank runs coupled with large-scale rupiah depreciation placed additional pressures on the balance sheet banks' balance sheet. Accordingly, such conditions led to a decline in the performance of national banks overall. The decline in performance affected all financial aspects of the banks, including capital, earning asset quality, earnings and liquidity. Capital dried up rapidly from the onset of the crisis, as reflected by a sharp decline in CAR for all banks from 9.19% at the end of December 1997 to -15.68% at yearend 1998. Similarly, the performance of earning assets (KAP), measured by comparing the amount of sub-standard earning assets against total earning assets, deteriorated rapidly from 4.80% at the end of 1997 to 42.39% at the end of 1998, before returning to around 12.74% at the end of 1999 as the credit from troubled banks was handed over to the Indonesian Bank Restructuring Agency (IBRA).

In line with the deterioration in KAP, earnings, measured by the return on assets (ROA), declined from 1.37% in 1997 to -18.76% in 1998 and -6.14% in 1999. The losses incurred by nearly all banks were attributable to the high cost of funds borne by the banks, coupled with interest rates on term deposits topping 70% in September 1998. Meanwhile, KAP increased and the amount of credit allocated declined in harmony with the economic contraction (13.1% in 1998) and escalation in business risk stemming from socio-political instability and the deteriorating domestic security situation. In line with the decline in credit, the bank loan to deposit ratio (LDR) also plummeted from 86.42% at the end of 1997 to 72.37% at yearend 1998 and just 26.16% at the end of 1999.

4. Data and Model

The Markov-Switching model applied in this paper uses latent variables that follow the first derivative from the two-state markov channel, namely $\{s_t\}_{t=1}^T$. $s_t=1$ denotes a crisis state and $s_t=0$ a tranquil state. In this model, however, s_t cannot be observed directly, but the behaviour of the dependent variable (y_t) is free from s_t , which can be expressed as follows:

$$y_t | s_t \sim N(\mu_{s_t}, \sigma_{s_t}^2) \quad (1)$$

The dependent variable (y_t), used as an early warning indicator of bank runs is the percentage change in bank deposits from 1990-2005. Therefore, this Markov-Switching (MS) model only uses a univariate model. The percentage change in deposits was chosen as a variable considering that bank runs are indeed large-scale fund withdrawals. Accordingly, signals of persistent withdrawals of bank deposits would indicate a run on the bank.

In the MS model, the mean and variance from y_t can change in line with the regime. The density of conditional s_t can be written as follows:

$$f(y_t | s_t) = \frac{1}{\sqrt{2\pi\sigma_{s_t}}} \exp \left[\frac{-(y_t - \mu_{s_t})^2}{2\sigma_{s_t}^2} \right]$$

for $s_t = 0,1$ (2)

The latent variable from the switching regime, s_t , can be obtained from the transition probability matrix P_t as follows:

		Period t	
		State 0	State 1
Periode t-1			
State 0		p'_{00} $\Pr(s_t = 0 s_{t-1} = 0, x_{t-1})$ $= F(x'_{t-1}\beta_0)$	$p'_{02} = (1 - p'_{00})$ $\Pr(s_t = 1 s_{t-1} = 0, x_{t-1})$ $= 1 - F(x'_{t-1}\beta_0)$
State 1		$p'_{10} = (1 - p'_{11})$ $\Pr(s_t = 0 s_{t-1} = 1, x_{t-1})$ $= 1 - F(x'_{t-1}\beta_1)$	p'_{11} $\Pr(s_t = 1 s_{t-1} = 1, x_{t-1})$ $= F(x'_{t-1}\beta_1)$

(3)

where p'_{ij} is the probability of changing from state i in period $t-1$ to state j in period t and F is the normal cumulative distribution function cdf component of vector $k \times 1$ and x_{t-1} is the early warning indicator that can influence the transition probabilities.

An initial value is required to start the model, namely $p_1^1 = \Pr(s_1 = 1)$, which is the unconditional probability of state 1 in period 1. The handling of this value depends on whether it is stationary or not x_t . If x_t is stationary then the long-term probability p_1^1 is $s_1 = 1$ and is a function of (β_0, β_1) . Meanwhile, if x_t is not stationary then p_1^1 is an additional parameter that must be estimated. In practice, if the time series data is long enough then the likelihood function will not be affected whether it is calculated using the function of (β_0, β_1) separately or the value is fixed, no significant changes occur.

The estimation procedure maximises the likelihood function. The likelihood function is calculated using the iteration developed by Hamilton (1990). Using available information up to period t , we can formulate $\Pr(s_t = j | \Omega_t; \Theta)$, namely the (filtered) conditional probability of observation i produced by regime j , for $j=1, 2, \dots, N$. N is the total state. In this research $N=2$. The conditional probability can subsequently be grouped in the vector $(N \times 1)$ $\hat{\xi}_{t|t}$.

The estimation can also be performed using (forecast) conditional probability produced by regime j in period $t+1$ with the information up to period t , which can be expressed as $\Pr(s_{t+1} = j | \Omega_t; \Theta)$, for $j=1, 2, \dots, N$. Estimating this probability The conditional probability can subsequently be grouped in the vector $(N \times 1)$ $\hat{\xi}_{t+1|t}$. Finally, η_t can be expressed as vector $(N \times 1)$, which has j components and represents the conditional density function from Equation (2). The filtered probability and calculation for each period t with the iteration from the equation is as follows:

$$\hat{\xi}_{t|t} = \frac{(\hat{\xi}_{t|t-1} \circ \eta_t)}{1'(\hat{\xi}_{t|t-1} \circ \eta_t)} \quad (4)$$

$$\hat{\xi}_{t+1|t} = P'_{t+1} \hat{\xi}_{t|t} \quad (5)$$

where P_t is the $N \times N$ matrix of transition probability from period $t-1$ to period t as found in Equation (4) and \circ is the multiplicative notation of each respective element. Equation (5) is used to solve $\Pr(s_t = j | \Omega_t; \Theta)$ as the joint distribution ratio $f(y_t, s_t = j | \Omega_t; \Theta)$ against the marginal distribution $f(y_t = j | \Omega_t; \Theta)$. The marginal distribution can be obtained by adding up the joint distribution of both states. Equation (5) indicates that with the best estimates for the current state,

we can simply multiply the transformation matrix P of the transition probability to find the probability of each state in the subsequent period. In additions, the transition probability is estimated using equations (6) through (41) as showed at attachment 2.

5. Empirical Results

As elaborated in Section 4, Markov-Switching and an auto-regressive approach were used to calculate the transition probability from a tranquil state to a state of bank runs as stated at equations (1) through (5), estimated using equations (6) through (41) at attachment 2. Estimations were performed using the variable of percentage change in deposits at individual banks (y). Data smoothing was used with a Kalman filter to ensure stationary data. Meanwhile, the validity of the MS model was tested as an early warning indicator of bank runs through a comparison with actual incidences of bank runs.

a. State-Owned Banks (BP)

Signals of bank runs in the Markov-Switching (MS) model can be observed from the transition probability value of changing from a tranquil state (no bank runs) to a state of bank runs. A value of more than 0.5 implies a greater then 50% chance of bank runs and a value of 1 means the probability has risen to 100%. Conversely, if the value is 0 then the probability of bank runs is zero. The results of the MS model for state-owned banks indicated vary rare incidences of signals of bank runs (Table 2). Such conditions are reflected by a transition probability from tranquil to crisis of 0 for nearly all months in the sample period. Of the 147 months under observation for each individual bank, only 16 indicated the potential occurrence of bank runs for BP1, 7 months for BP2, 5 months for BP3, 4 months for BP4 and 5 months for BP5, with values in the range of 0.7 to 1. However, these signals of bank runs were not persistent as reflected by a drop in value from 0.7-1 down to 0 (Attachment 2) in the subsequent months.

Meanwhile, during the banking crisis from 1997-1998, the MS model did not generate any signals of runs on state-owned banks, as evidenced by a transition probability value of 0 during the period in question. Comparing the test results against actual incidences of bank runs during the 1997-1998 period shows that the MS model was able to accurately detect bank runs.

During the observation period from January 1988 - March 2000 for five state-owned banks, only six months (0.82%) produced erroneous signals of bank runs (type 2 error).⁶

Table 2 Results of Markov-Switching for State-Owned Banks

No	Bank	Date of Bank Runs
1	BP1	Apr, May, Aug & Nov-88, Jan, Apr, Jul, Aug & Oct-89, Jan, Apr, Jul & Aug-90, Feb & Mar-91, Sept-94
2	BP2	Apr & Des-91, Oct Nov 92, Des-99, Jan & Feb-00
3	BP3	Mar & Apr-91, Oct, Nov & Des-99
4	BP4	Mar, Apr & Des-91, Sept-94
5	BP5	Aug-89, Mar, Apr, May & Jul-90

b. Foreign Exchange Banks (BSD)

Based on analysis results for 26 private foreign exchange banks (BSD) using the MS model, signals of bank runs were a common occurrence for 7 banks (Table 3). Such conditions were evidenced by a transition probability value for each bank in the range of 0.8 to 1, with the value persisting for a number of months. Based on a review of actual incidences of bank runs, in particular during the banking crisis of 1997-1998, all seven of the banks experienced runs. In the periods before and after 1997-1998, all seven of the banks also indicated signals of bank runs with a transition probability value in the range of 0.7 to 1 (Attachment 2).

Conversely, the results of Markov-Switching indicated that 12 banks did not display signals of runs, as demonstrated by a transition probability value of zero. Other foreign exchange banks only produced sporadic signals of bank runs and the signals did not persist over several months. Of the total 216 months observed (January 1988 – December 2005) and 26 banks, only 57 months were found to produce erroneous signals (1.01%).⁷

⁶ The measure of actual bank runs was determined by a bank that experienced a bank run as well as banks that encountered liquidity difficulties as a result of large-scale withdrawals by their customers. A value of 0.82% was obtained from all false signals divided by total months for 5 banks, namely 6 divided by 735.

⁷ Calculated from total erroneous signals divided by the number of months in the observation period multiplied by the number of banks in the sample. Therefore, the value of 1.01% is obtained from 57/(216 x 26).

Table 3 Results of Markov-Switching for Private Foreign Exchange Banks

No	Bank	Date of Bank Runs
1	BSD5	Aug-90, Sept-91, Aug, Sept & Des97, Jan, Feb & Mar-98, Aug & Des-00, Nop & Des-00, Jan, May, Jul & Aug-02, Aug-03, Sep-04
2	BSD10	Aug-90, Jun, Jul, Nov & Des-92, Jan-93, Oct & Nop-97, Jan, Feb & Mar-98, Feb, Sept, Oct, Nov & Des-99, Feb, Mar, Apr, May, Jun & Jul-00, Jan, Aug, Sept & Oct-01, Aug-02, Aug-03
3	BSD19	Des-88, Oct-89, Jan, Feb & Sept-90, Nov & Des-97, Jan, Mar Apr, Jun, Jul & Aug-88, Mar, Apr Jun, Jul & Aug-99, Apr & May-00, Jul & Oct-02, Jan, Apr, Jun & Aug03, Des-04, Jan & Nov-05
4	BSD22	Oct-95, Aug & Sept-98, Mar, Jun & Jul-99, Sept & Nov-02, Feb, Mar, Aug, Oct & Nov-03, Jan, Apr, May, Nov & Des-04
5	BSD23	Des-97, Jan, May, Jun, Jul, Sep & Nov-98, Jan, Feb, Mar, Apr, Jul, Aug, Oct & Des-99, Jan, Feb, Mar & Apr-00, Nov & des-02, May & Aug-03, Nov-05
6	BSD24	Feb, Apr, Jun, Aug & Oct-91, Sept & Des-92, Mar-93, Feb, Mar, Apr, Jun, Jul & Aug-98, Jul-00, Aug & sept-02, Jan-Oct & Nov-05
7	BSD26	Sep-88, Oct & Nov-92, Jan, Apr & Jun93, Jul-96, Jun & Jul-98, Mar, Jul & Aug-99, Jan, Jul, Aug, Oct, Nov & Des-03, Feb-05

c. Private Non Foreign Exchange Banks

The results of Markov-Switching showed that of the 31 private non foreign exchange banks under observation, as many as 20 signalled frequent bank runs with a transition probability value in the range of 0.8 to 1 (Table 4). A comparison with what actual occurred shows that the 20 banks faced severe bank runs in 1997-1998. Prior to experiencing bank runs in 1997-1998, the 20 banks also showed persistent signals of bank runs as indicated by the probability value in the range of 0.9 to 1. Similar signals persisted until the year 2000, with the magnitude easing slightly in the range of 0.8 to 1.

Meanwhile 11 other non-foreign exchange banks also generated signals of bank runs, but less frequently than the 20 banks mentioned previously. Furthermore, the transition probability value was lower for these 11 banks in the range of 0.6 to 1 (Attachment 2). During the banking crisis in 1997-1998, the 11 banks did not suffer bank runs. When compared to what actually happened, Markov-Switching produced erroneous signals for 94 months (1.4%).

Therefore, the MS model can be considered sufficiently accurate in the detection of runs on non-foreign exchange banks.

Table 4 Results of Markov-Switching for Private Non Foreign Exchange Banks

No	Bank	Date of Bank Runs
1	BSND2	Des-88, Jul, Oct & Des-93, Feb, Apr, Jul & Sept-95, Nov-Des-97, Jan-98
2	BSND3	Des-88, De93, Nov & Des-94, Feb, Mar, Apr, Jun & Sept-95, Feb & Mar99, Oct & Nov-01, Des-02, Des-03 Des-04, Jan, Jun & Jul-05
3	BSND6	Mar, Nov & Des-88, Des-93, Jan, Sept, Oct, Nov & Des-94, Feb, Mar, Apr, Jun, Aug & Sept-95, Nov & Des-97, Mar-99, Nov-01
4	BSND7	Mar, Jun, Sept & Des-88, Oct-89, Nov & Des-93, Des-94, Apr, Jul, Aug & Sept-95, Oct & Nov-97, Jan-98, Feb, Mar, May, Jun, Jul, Aug & Nov-99, Oct, Nov-01, Jan-03, Jan-04, Jan-05
5	BSND9	Mar, Jul, Nov & Des-88, Jan-90, Apr-92, Jul-93, Des94, Apr & Sept-95, Nov & Des-97, Feb-99
6	BSND10	Mar, Jun & Nov-88, Jan, Apr, Jul, Oct & Des-91, Feb, Apr, Jul, Aug, Oct & Nov-92, Jan, Feb, Apr, May, Jul & Sept-93, Mar, Apr, Sept, Nov & Des-94, Feb, Mar, Apr, Aug & sept-95, Des-97, Jul-98, Feb, Mar Jul & Oct-99
7	BSND11	Aug, Sept & Oct-88, Jan, Aug & nov-91, Apr, May, Jun, Jul, Aug, Sept & Des-92, Feb, Apr, May, Jul, Nov & Des-93, May, Jul, Sept, Oct & Des-94, Feb, Apr, Jun & Sept-95, Feb, Apr, May Jun, Jul, Nov & Des-96, Jul, Sept & Nov-97, May, Jun, Aug, Sep, Oct & Des-99, Jun-00
8	BSND14	Des-91, Des-93, Feb, Apr, Nov & Des-94, Mar, Apr, Jul & Sept-95, Jan, Aug, Sept, Nov & Des-97, Apr, May, Jul Oct-98, Mar, Apr & May-99
9	BSND16	May & Jul-88, Jul, Nov & Des-93, Jul, Sept & Oct-97, Des-98, Jan, Mar, Apr & May-99
10	BSND17	May-88, Nov-92, Feb, Jul, Sept & Des-93, Mar, Apr, Jun & Des94, Feb, Mar, Apr, Jun & Sept-95, Aug, Sept & Oct-97, May, Aug, Sept, Oct & Des-98, Jan, Apr, May, Aug & Oct-99, Jan,, Feb, Mar, May-00
11	BSND18	Jun, Jul, Oct & Nov-88, Jan-92, Jun, Jul, Sept, Nov & Des-93, Nov & Des-94, Mar, Apr & Sept-95, Jan, Mar, Jun, Aug, Oct & Nov-98, Jan, Feb & Mar-99
12	BSND19	May, Jul, Sept & Nop-88, Jan, Apr & May-92, Jan, Feb, Jul, Sep, Oct & Des-93, Jan, Feb, Mar, Apr, Jul, Aug, Sept & Des-94, Feb, Jun, Jul & Sept-95, Mar, Apr, Jul, Sept Nov-96, Jan, Feb, Apr, Jul, Aug, Sept, Oct & Nov-97, Mar, Apr, Jun, Sept, Oct & Nov-98, Jan, Apr Sept & Oct-99, Feb & Jul-00
13	BSND20	Jul & Aug-88, Jan, Apr, Jul & Aug92, Feb, Apr, Jul, Aug & Des-93, Mar, Apr, May, Jul, Sept & Des-94, Mar, Apr & Sept-95, Mar & Nop-96, Jan, May, Jun, Jul & Oct97, Jan, Jun, Jul, Aug, Sept, Oct & Nov-98, Jan, Feb, Mar, Jul, Sept & Oct-99
14	BSND21	Mar, May, Jul, Oct & Nov-88, Oct-92, Mar & Des-93, Nov & Des94, Apr, Jul & Sept-95, Des-97, Jan-98, Feb-99, Jul-00
15	BSND22	Mar & Jul-88, Jan, Jul, Sept & Des-93, Mar, May, Jul, Aug & Des-94, Mar, Apr, Jun, Jul, Aug, Sept, Nov & Des-95, Mar, May, Jun, Jul, Oct & Des-96, May, Oct & Nov-97, Mar, May, Aug, Nov & Des-98, Jan, Mar, May, Jun, Jul, Sept & Des99, Jan, Feb & Mar-00

16	BSND25	Mar, May & Jun-88, Oct & Des-93, Oct & Des-94, Jan, Apr, Jul & Sept-95, Oct & Nov-97, Jan, May, Jul, Aug, Sep, Oct & Des-98, Apr & Jul99
17	BSND26	Sep & Nop88, Jan, Jul & Des-93, Mar, Aug, Oct & Des-94, Jan, Apr, Sept & Des-95, Mar-96, Feb, Oct & Nov-97, Jan, May, Jun & Aug-98, Jan, Mar, Jul & Des-99, Feb, Mar, May & Jun-00
18	BSND27	Jul & Sept-98, Jan & Jul-93, Apr & Des-94, Apr, Sept & Nov-95, Jan, Feb, Apr, May, Jun, Jul, Sept, Oct, Nov & Des-96, Sept & Des-97, Jan, May, Jul, Sept & Des-98, Feb, Mar, Apr, May, Aug, Nov & Des99, Jul-00
19	BSND29:	May, Jun, Jul & Nov-88, Mar, Jun, Aug, Nov & Des-94, Feb, Apr, Jul, Aug & Sept-95, Aug, Sept, Oct & Nov-97, Apr, May, Aug, Sept Nov-98, Feb, Mar, May, Jun, Jul, Sept & Oct-99, Mar-00
20	BSND31:	Apr, Jul & Des-94, Mar, Apr, Sept, Nov & Des-95, Jan, Apr, May, Aug, Oct & Nov-96, Feb, Apr, Aug, Nov & Des-97, Jun, Aug, Oct Des-98, Jan, Apr, May & Aug-99, Feb, Mar & Jun-00

d. Foreign Banks

The results of Markov-Switching (MS) showed that four out of the six foreign banks tested often produced signals of bank runs with a transition probability value in the range of 0.6 to 1 (Table 5). During the banking crisis in 1997/1998 and based on the MS model, the four banks in question experienced bank runs. In contrast, the two remaining foreign banks did not produce signals of bank runs as indicated by a transition probability value of zero (Attachment 2). Actual experience shows that neither bank was prone to runs.

Holistically, of all the data observed for the period from January 1988 to December 2005, the MS model produced erroneous signals for 27 months or 2.08% of the total six banks over 216 months. Therefore, the signals produced by the MS model were sufficiently accurate in the determination of runs on a particular foreign bank.

Table 5 Results of Markov-Switching for Foreign Banks

No	Bank	Date of Bank Runs
1	BA1	Jan, Apr, May, Sept & Des-90, Jan, Feb, Mar, Jun & Jul-91, Jul & Sept-97, Jun, Jul, Aug & Sept-98, Jan, Aug, Sept & Oct-02, Jan, Feb & May 03, Jan, Mar, Apr, Aug & Nop-04, Fe, Jun, Jul & Aug-05
2	BA2	Feb, May, Sep, Oct & Nop-89, Jan, Mar, Apr, Jun, Jul, Aug & Oct-90, Jan, Apr, Aug, Sept & Nop-93, Jan, Apr, Aug, Sept & Nop-93, Feb, Mar, Apr, Jul, Oct & Des-95, Jan Feb, Mar, Apr & Aug 96, Jan, Mar, Apr, Jun, Jul, Aug & Oct-97, Feb, Jul, Aug, Sept & Nop-98, Feb, May, Jun & Aug-00, Jan, Feb, Mar, Jun, Jul, Aug, Oct & Des-01, Jan, Feb, Mar, Apr, Jul, Aug, Oct-02, Apr, May & Jul-03, Jan, Feb, Mar, Apr, Jun, Sep & Oct-04, Jan, Feb, Mar, Apr & Aug-05
3	BA3	Apr, Jul & Des-93, Feb, Mar, May, Jun, Sept, Oct & Nov-94, Jan, Mar, Apr, Apr, Jul, Aug & Oct-95, Feb, Mar, May, Jun & Aug-96, Feb, Aug, Sept, Oct-97, Apr, Jun, Jul, Aug, Sept, Oct & Des-98, Jun-99, Feb-02, Jul, Sept &

		Oct-04, Jan, Jun & Jul-05
4	BA4	Jun, Aug, Oct & Des-89, Jan, Apr, May, Jun & Aug-90, May, Aug, Oct & Des-93, Feb & Mar-94, Jul, Oct & Des-95, Feb & Mar-96, Jun & Oct-97, Apr, Jun, Jul & Aug-98, May, Jun & Aug-05

e. Joint Venture Banks (BC)

The results of the MS model for the nine joint venture banks observed showed indications of bank runs during the banking crisis in 1997-1998, with a transition probability value of 1, denoting a 100% chance of bank runs. This is congruous with what actually happened, where all nine banks experienced runs. Meanwhile, in terms of frequency, four banks regularly suffered runs (Table 6) with a probability value in the range of 0.7 to 1.

A comparison with what actually transpired shows that the MS model produced false signals for 18 months or 0.93% of the total banks and months observed. The results of Markov-Switching for joint venture banks demonstrated that the model is sufficiently accurate when used as an early warning indicator of bank runs at respective individual banks.

Table 6 Results of Markov-Switching for Joint Venture Banks

No	Bank	Date of Bank Runs
1	BC2	Apr, Aug, Oct, Nov & Des-90, Feb, Mar, Apr, May, Aug, Sept & Nov-91, Jan, Mar, Jul, Aug & Oct-92, Jan, Feb, May, Jul, Aug & Oct-93, Jan, Mar, Apr, Jun, Jul, Aug & Oct-94, Jan, Feb, Mar-95, Sep, Oct, Nov & Des-96, Feb, Mar, Apr, May, Aug & Nov-97, Feb, Mar, Apr, Jul, Oct, Nov & Des-98, Jan, Feb, Apr, May & Aug-99, Sept-04, Jan, Feb, May-05
2	BC5	May, Aug & Nop90, Mar, Apr, May, Jul & Oct-91, Jan, Apr, May, Jun, Jul & Aug-04, Aug, Sept & Nov-97, Feb, Apr, Jun, Jul & Sept-98
3	BC6	Des-89, Jan, Apr, May, Jul, Aug, Oct, Nov Des-90, Jan, Apr, May, Jun, Nov & Des-91, Jan, Apr, Jun, Aug & Oct-92, Jan, Apr, May, Jun, Jul, Oct & Des-93, Mar, Apr, Jul, Aug, Oct, Nov & des-94, Feb, Mar, Apr, Jun, Jul, Sept, Oct & Des-95, Jan, Mar, Apr, Jul, Aug & Des-96, Feb, Jul, Sept & Oct-97, Jan, Mar, Apr, May, Jul, Sept, Oct, Nov & Des-97, Feb, Mar, Apr, Jun, Jul & Des-99, Feb, Mar, Jun, Jul, Aug & Des-00, Jan-01
4	BC7	Jul & Oct-90, Jan, Apr, May, Jun, Aug & Nov-91, Jan, Sept & Oct-92, Jan, Feb, Mar, Apr, May, Jun, Jul, Aug, Sept & Oct-93, Mar, Apr & May-94, Apr, Jun, Aug, Oct, Nov & Des-95, Jan, Mar, May, Jun, Sept, Oct & Nov-96, Jan,

		Mar, May, Jun, Sep, Oct & Nov-97, Apr, Jun, Jul, Oct & Nov-98, Mar, Jun, Aug-99, Mar, May, Jul & Aug-03, Jan, Mar, Apr & Des-04, Apr, Jun & Jul-05
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f. Banks with Frozen Business Activity (BBKU)

Of the eight banks with frozen business activity analysed using the MS model, only two did not produce signals of bank runs during the banking crisis in 1997-1998, while the five other banks did (Table 7) with a probability value in the range of 0.9 to 1. BBKU 2 and 3 often produced signals of bank runs, with a transition probability value in the range of 0.9 to 1 (Attachment 2). Such conditions are in harmony with what actually occurred during the observation period.

When compared to what happened in actuality based on a full sample, there remain 12 months of erroneous signals or 0.69% of total observations. The false signals were produced by just four banks, therefore, the MS model is sufficiently robust for use as an indicator to detect runs on troubled banks as well as an indicator of supervision on other individual banks.

Table 7 Results of Markov-Switching for Banks with Frozen Business Activity (BBKU)

No	Bank	Date of Bank Runs
1	BBKU1	Aug-89
2	BBKU2	Aug & Oct-89, Jan, Jul, Aug & Nop-90, Jan, Feb, Apr, Jul, Aug & Oct-91, Des-92, Jan, Jul & Aug-93, Jan-94, Oct, Nov & Des-98
3	BBKU3	Mar & Nop-88, Jul & Aug-90, Jul, Aug & Des-91, Oct, Nov & Des-92, Nov 98
4	BBKU4	Nov-88, Jul & Aug-90, Nov & Des-92, Des-93, Des-98
5	BBKU5	Aug-89, Sep-92, Des-93, Sep & Oct-94, Feb, Apr & Jun-96
6	BBKU6	Oct, Nov & Des-88, Jan & Oct-89, Des-98
7	BBKU7	Mar, May, Jun, Aug, Sep, Oct, Nov & Des-98
8	BBKU8	Apr, May, Sep, Oct, Nov & Des-98

g. Banks with Frozen Operations (BBO)

The results of the MS model show that of the seven frozen banks (BBO) under observation, six produced signals of bank runs during the banking crisis period of 1997-1998, as

reflected by the value of transition probability totalling 1. The six BBO also regularly generated signals of bank runs prior to the crisis (Table 8). One other bank, BBO6, only produced signals of a bank run in 1993.

The results of the comparison with real events show that the MS model successfully explains the phenomena of runs on banks that had their operations frozen during the period of 1997-1998 in Indonesia. From all of the observations, only 19 times were erroneous signals produced or 1.26%.

Table 8 Results of Markov-Switching for Banks with Frozen Operations (BBO)

No	Bank	Date of Bank Runs
1	BBO1	Aug, Oct & Nop-88, Jul & Aug-89, Des-97, Jan, Apr, May & Jun-98
2	BBO2	Aug & Nop-89, Feb-93, Nov & Des97, Jan, Feb, Mar, Apr, May & Jun-98
3	BBO3	Aug & Nov-88, Aug & Des-89, May & Aug 90, Sep, Oct & Des-97
4	BBO4	Aug-90, Jan, Feb & Apr-91, Jun-92, Des-94, Des-97, Jan-98
5	BBO5	Des-92, Aug, Sep, Oct & Des-97, Feb, Mar & Jun-92, Aug, Sep, Oct & Des-97, Jan-98
6	BBO6	Feb, Mar & Jun-93
7	BBO7	Apr, Sept, Oct & Nov-92, Jan, Apr, Oct & Nov-93, Jan, Feb, May, Aug & Nov-94, Feb, Sep & Des-95, Feb-96, Jan, Apr, Aug Sept, Oct & Des-97, Jan-98

6. Conclusions and Policy Implications

- a. The results of Markov-Switching (MS) demonstrate that the MS model is robust as an early warning indicator of bank runs on the strength of testing against what actually happened at 102 banks with erroneous signals produced in just 0.69% to 2.08% of cases.
- b. Early warning indicators of bank runs using the MS model showed that those banks prone to runs and troubled banks persistently signalled bank runs in estimations using the model. The monthly model could be developed further to become a daily model used to detect the probability of bank runs. To this end, the MS model is recommended as a tool to detect bank runs within the supervision cycle of individual banks according to the risk-

based supervision applied in Indonesia. The early warning indicators (EWI) produced by the MS model in the supervision cycle are equally important as the risk-profile assessment of each respective bank, thus EWI information can synergised with the assessment of bank business risk in order to prevent future occurrences of bank runs or other problems that threaten the business continuity of the banking industry.

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Markov-Switching Estimation

This appendix explains in detail the estimation process of transitional probabilistic value that is used as early warning indicators (EWI) of bank runs. In principle, our Markov-switching estimation model is an MS autoregressive model developed by Hamilton (1990). We use the percentage value of changes in deposit/third party fund (y_t) as the early warning indicator variable. It is assumed that y_t follow an AR(3)⁸ process where the parameter can change from a normal state (where there are no bank runs) to the state where there are bank runs. We can write the autoregressive process of y_t as

$$y_t = \alpha_{s_t} + \phi_{1,s_t} y_{t-1} + \phi_{2,s_t} y_{t-2} + \phi_{3,s_t} y_{t-3} + \varepsilon_t \quad (6)$$

With $\varepsilon_t \sim N(0, \sigma_{s_t}^2)$.

If we write the above equation in a more compact form, we will have the following expression

$$y_t = x_t' \beta_{s_t} + \varepsilon_t \quad (7)$$

With

$$x_t \equiv (1, y_{t-1}, y_{t-2}, y_{t-3})' \quad (8)$$

$$\beta_{s_t} \equiv (\alpha_{s_t}, \phi_{1,s_t}, \phi_{2,s_t}, \phi_{3,s_t}) \quad (9)$$

The distribution function of equation (7) can be written as

$$p(y_t | z_t; \theta) = \frac{1}{\sqrt{2\pi} \sigma_{s_t}} \exp \left\{ -\frac{(y_t - x_t \beta_{s_t})^2}{2\sigma_{s_t}^2} \right\} \quad (10)$$

The log-likelihood function of equation (7) is

$$\log p(y_t | z_t; \theta) = -\frac{1}{2} \log 2\pi - \frac{1}{2} \log \sigma_{s_t}^2 - \frac{(y_t - x_t \beta_{s_t})^2}{2\sigma_{s_t}^2} \quad (11)$$

FOC that maximizes the above log-likelihood function is

⁸ We use AIC and SBC to determine the optimal lag length.

$$\frac{\partial \log p(y_t | z_t; \theta)}{\partial \beta_j} = -2 \frac{y_t - x_t' \beta_j}{2\sigma_j^2} x_t = \frac{(y_t - x_t' \beta_j) x_t}{\sigma_j^2}, s_t = j$$

$$= 0, \text{ otherwise}$$

And

$$\frac{\partial \log p(y_t | z_t; \theta)}{\partial \sigma_j^2} = -\frac{1}{2} \frac{1}{\sigma_j^2} + \frac{(y_t - x_t' \beta_j)^2}{2\sigma_j^4}$$

According to Hamilton, the likelihood function of the above expression is

$$L(\theta) = \sum_{t=1}^T \log p(y_t | z_t; \theta) \quad (12)$$

If we define

$$Y = (y_T, y_{T-1}, \dots, y_1)' \quad (13)$$

$$S = (s_T, s_{T-1}, \dots, s_1)' \quad (14)$$

Following Hamilton (1990), we can write the joint marginal distribution of the two states as

$$p(Y; \theta) = \int_S p(Y, S; \theta) \quad (15)$$

We can define a new function which defined as the expectation of the log-likelihood

$$Q(\theta_{i+1}; \theta_i, Y) = \int_S \log p(Y, S; \theta_{i+1}) \cdot p(Y, S; \theta_i) \quad (16)$$

This function is very useful in the process of maximizing the log-likelihood. According to Hamilton, the FOC condition is satisfied if

$$\frac{\partial Q(\theta_{i+1}; \theta_i, Y)}{\partial \theta_{i+1}} = \int_S \frac{\partial \log p(Y, S; \theta_{i+1})}{\partial \theta_{i+1}} \cdot p(Y, S; \theta_i) = 0$$

Hamilton (1990) proved that the above expression satisfied the FOC that maximize the log-likelihood function.

The log-likelihood function is maximized by defining the following Lagrange function

$$J(\theta) = L(\theta) + \lambda(1 - \pi_1 - \pi_2 - \dots - \pi_k) \quad (17)$$

Using this function we will get

$$\begin{aligned}
1. \quad \frac{\partial J(\theta)}{\partial \beta_j} &= \frac{\partial L(\theta)}{\partial \beta_j} = \sum_{t=1}^T \frac{p(y_t, s_t = j; \theta)}{p(y_t; \theta)} \frac{(y_t - x_t' \beta_j) x_t}{\sigma_j^2} \\
&= \sum_{t=1}^T \frac{(y_t - x_t' \beta_j) x_t}{\sigma_j^2} p(s_t | y_t; \theta) = 0
\end{aligned} \tag{18}$$

By multiplying the denominator with 0 we will get

$$\sum_{t=1}^T (y_t - x_t' \beta_j) x_t p(s_t = j | y_t; \theta) = 0 \tag{19}$$

We can solve the above equation with

$$\sum_{t=1}^T y_t x_t p(s_t = j | y_t; \theta) - \beta_j \sum_{t=1}^T x_t' x_t p(s_t = j | y_t; \theta) = 0 \tag{20}$$

$$\begin{aligned}
\hat{\beta}_j &= \left[\sum_{t=1}^T x_t' x_t p(s_t = j | y_t; \theta) \right]^{-1} \sum_{t=1}^T y_t x_t p(s_t = j | y_t; \theta) \\
\hat{\beta}_j &= \left[\sum_{t=1}^T x_t^*{}' x_t^* \right]^{-1} \sum_{t=1}^T x_t^* y_t^*
\end{aligned} \tag{21}$$

Where $x_t^* = x_t \sqrt{p(s_t = j | y_t; \theta)}$ and $y_t^* = y_t \sqrt{p(s_t = j | y_t; \theta)}$

$$\begin{aligned}
2. \quad \frac{\partial}{\partial \sigma_j^2} J(\theta) &= \frac{\partial}{\partial \sigma_j^2} L(\theta) = \sum_{t=1}^T \frac{p(y_t, s_t = j; \theta)}{p(y_t; \theta)} \left\{ -\frac{1}{2\sigma_j^2} + \frac{(y_t - x_t' \beta_j)^2}{2\sigma_j^4} \right\} \\
&= \sum_{t=1}^T \left\{ -\frac{1}{2\sigma_j^2} + \frac{(y_t - x_t' \beta_j)^2}{2\sigma_j^4} \right\} p(s_t = j | y_t; \theta) = 0
\end{aligned} \tag{22}$$

By solving the above equation we will get

$$\hat{\sigma}_j^2 = \frac{\sum_{t=1}^T (y_t - x_t' \hat{\beta}_j)^2 p(s_t = j | y_t; \theta)}{\sum_{t=1}^T p(s_t = j | y_t; \theta)} \tag{23}$$

$$\begin{aligned}
3. \quad \frac{\partial}{\partial \pi_j} J(\theta) &= \frac{\partial}{\partial \pi_j} L(\theta) = \sum_{t=1}^T \frac{p(y_t, s_t = j; \theta)}{p(y_t; \theta)} - \lambda \\
&= \sum_{t=1}^T \frac{p(y_t | s_t = j; \theta) p(s_t = j; \theta)}{p(y_t; \theta)} - \lambda = 0, \\
s_t = j &\Rightarrow p(s_t = j; \theta) = 1
\end{aligned} \tag{24}$$

By solving the above equation we will get

$$\sum_{t=1}^T \frac{p(y_t | s_t = j; \theta)}{p(y_t; \theta)} - \lambda = \pi_j^{-1} \sum_{t=1}^T \frac{p(y_t, s_t = j; \theta)}{p(y_t; \theta)} - \lambda = \pi_j^{-1} \sum_{t=1}^T p(s_t = j | \theta) - \lambda = 0 \quad (25)$$

We can simplify the above equation into the following expression

$$\sum_{t=1}^T p(s_t = j | \theta) = \lambda \pi_j \quad (26)$$

Summing for $j=1,2,\dots,k$, we will get

$$\sum_{t=1}^T \sum_{j=1}^K p(s_t = j | \theta) = \lambda \sum_{j=1}^K \pi_j$$

$$\sum_{t=1}^T \{1\} = \lambda \cdot 1 \Rightarrow \lambda = T$$

Because $\sum_{j=1}^K p(s_t = j | \theta) = 1$ and $\sum_{j=1}^K \pi_j = 1$. We will get the estimator by

$$\hat{\pi}_j = \frac{1}{T} \sum_{t=1}^T p(s_t = j | \theta) \quad (27)$$

Based on Hamilton (1990), we can prove that the following transitional distribution satisfied the FOC

$$p_{ij}^{n+1} = \frac{\sum_{t=1}^T p(s_t = j, s_{t-1} = i | y_t; \theta)}{\sum_{t=1}^T p(s_{t-1} = i | y_t; \theta)} \quad (28)$$

The algorithm for estimating the parameter with arbitrary initial value is

$$p(y_t | Y_{t-1}) = \sum_{s_t=1}^K \sum_{s_{t-1}=1}^K p(s_t | s_{t-1}) p(y_t | s_t) \rho_{s_{t-1}} \quad (29)$$

$$p(s_t, s_{t-1} | y_t) = \frac{p(s_t | s_{t-1}) p(y_t | s_t) p(s_{t-1} | y_{t-1})}{p(y_t | Y_{t-1})} \quad (30)$$

$$= \frac{p(s_t | s_{t-1}) p(y_t | s_t) \rho_{s_{t-1}}}{p(y_t | Y_{t-1})}$$

$$p(s_{t-1} | y_t) = \sum_{s_t=1}^K p(s_t, s_{t-1} | y_t) \quad (31)$$

$\rho_{s_{t-1}} = p(s_{t-1} | y_{t-1})$ is taken from the previous value with $\rho_{s_0} = p(s_0 | y_0)$ as the initial value.

The latter value is randomly selected and used as the initial value in the estimation process.

For the *two-state markov change regime* case as used in this paper, the transitional probability value can be calculated using the following equation:

$$p_{11}^{n+1} = \frac{\sum_{t=1}^T p(s_t = 1, s_{t-1} = 1; \theta)}{\sum_{t=1}^T p(s_{t-1} = 1; \theta)} \quad (32)$$

$$p(s_t = 1, s_{t-1} = 1 | y_t) = \frac{p(s_t = 1 | s_{t-1} = 1)p(y_t | s_t = 1)p(s_{t-1} = 1 | y_{t-1})}{p(y_t | Y_{t-1})} \quad (33)$$

$$p(s_t = 2, s_{t-1} = 1 | y_t) = \frac{p(s_t = 2 | s_{t-1} = 1)p(y_t | s_t = 2)p(s_{t-1} = 1 | y_{t-1})}{p(y_t | Y_{t-1})} \quad (34)$$

$$p(s_t = 1, s_{t-1} = 1 | y_t) = \frac{p_{11}^n \eta_{t|s_t=1} \rho_{s_{t-1}}^n}{p(y_t | Y_{t-1})} \quad (35)$$

$$\begin{aligned} & \begin{bmatrix} p(s_t = 1, s_{t-1} = 1 | y_t) & p(s_t = 2, s_{t-1} = 1 | y_t) \\ p(s_t = 1, s_{t-1} = 2 | y_t) & p(s_t = 2, s_{t-1} = 2 | y_t) \end{bmatrix} \\ & = \left\{ \begin{bmatrix} \rho_{s_0=1} & 0 \\ 0 & \rho_{s_0=2} \end{bmatrix} \begin{bmatrix} p_{11} & p_{12} \\ p_{21} & p_{22} \end{bmatrix} \begin{bmatrix} \eta_{t|s_t=1} & 0 \\ 0 & \eta_{t|s_t=2} \end{bmatrix} \right\} / p(y_t | Y_{t-1}) \end{aligned}$$

$$p(y_t | Y_{t-1}) = \sum_{s_t=1}^K \sum_{s_{t-1}=1}^K p_{ij}^n \eta_{t|s_t} \rho_{s_{t-1}}^n = \begin{bmatrix} \rho_{s_0=1} & \rho_{s_0=2} \end{bmatrix} \begin{bmatrix} p_{11} & p_{12} \\ p_{21} & p_{22} \end{bmatrix} \begin{bmatrix} \eta_{t|s_t=1} \\ \eta_{t|s_t=2} \end{bmatrix} \quad (36)$$

$$p(s_{t-1} = 1 | y_t) = \sum_{s_t=1}^K p(s_t, s_{t-1} = 1 | y_t) \quad (37)$$

$$p(s_{t-1} = 1 | y_t) = p(s_t = 1, s_{t-1} = 1 | y_t) + p(s_t = 2, s_{t-1} = 1 | y_t) \quad (38)$$

$$\begin{aligned} p(s_{t-1} = 1 | y_t) &= \frac{[p(s_t = 2 | s_{t-1} = 1)p(y_t | s_t = 2) + p(s_t = 1 | s_{t-1} = 1)p(y_t | s_t = 1)]p(s_{t-1} = 1 | y_{t-1})}{p(y_t | Y_{t-1})} \\ &= \frac{[p_{12} \eta_{t|s_t=2} + p_{11} \eta_{t|s_t=1}]p(s_{t-1} = 1 | y_{t-1})}{p(y_t | Y_{t-1})} \end{aligned} \quad (39)$$

$$\begin{aligned}
\begin{bmatrix} p(s_{t-1} = 1 | y_t) \\ p(s_{t-1} = 2 | y_t) \end{bmatrix} &= \begin{bmatrix} p(s_t = 1, s_{t-1} = 1 | y_t) & p(s_t = 2, s_{t-1} = 1 | y_t) \\ p(s_t = 1, s_{t-1} = 2 | y_t) & p(s_t = 2, s_{t-1} = 2 | y_t) \end{bmatrix} \begin{bmatrix} 1 \\ 1 \end{bmatrix} \\
&= \begin{bmatrix} p(s_t = 1, s_{t-1} = 1 | y_t) + p(s_t = 2, s_{t-1} = 1 | y_t) \\ p(s_t = 1, s_{t-1} = 2 | y_t) + p(s_t = 2, s_{t-1} = 2 | y_t) \end{bmatrix} \quad (40)
\end{aligned}$$

$$p_{11}^{n+1} = \frac{\sum_{t=1}^T \frac{p_{11} \eta_{t|s_t=1} p(s_{t-1} = 1 | y_{t-1})}{p(y_t | Y_{t-1})}}{\sum_{t=1}^T \frac{(p_{12} \eta_{t|s_t=2} + p_{11} \eta_{t|s_t=1}) p(s_{t-1} = 1 | y_{t-1})}{p(y_t | Y_{t-1})}}$$

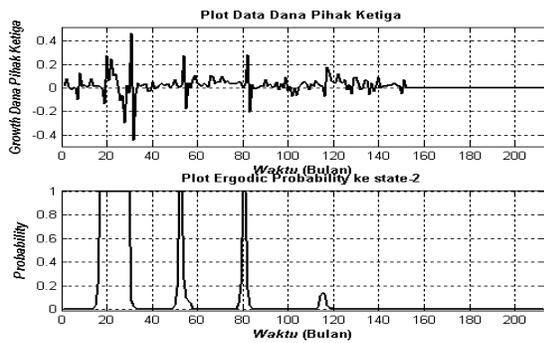
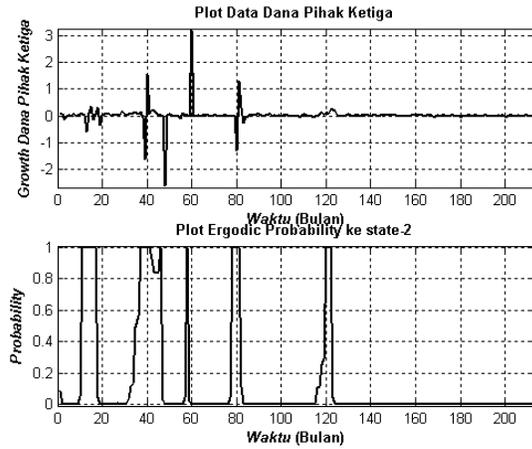
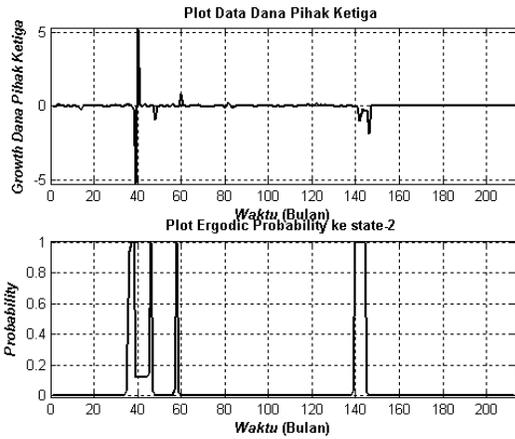
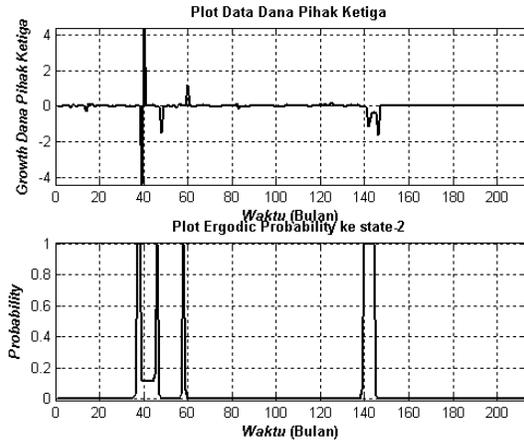
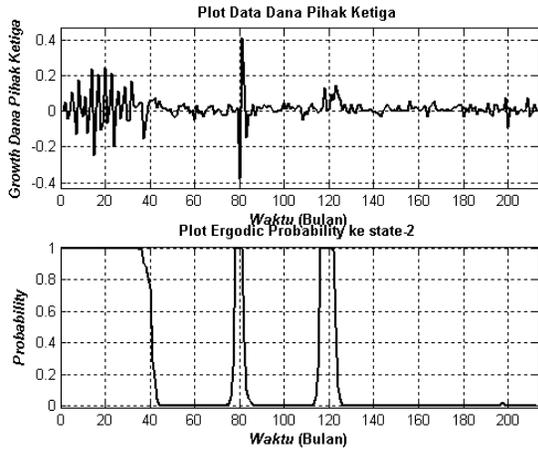
$$= \begin{bmatrix} p(s_t = 1, s_{t-1} = 1 | y_t) & p(s_t = 2, s_{t-1} = 1 | y_t) \\ p(s_t = 1, s_{t-1} = 2 | y_t) & p(s_t = 2, s_{t-1} = 2 | y_t) \end{bmatrix} \begin{bmatrix} [p(s_t = 1, s_{t-1} = 1 | y_t) + p(s_t = 2, s_{t-1} = 1 | y_t)]^{-1} & 0 \\ 0 & [p(s_t = 1, s_{t-1} = 2 | y_t) + p(s_t = 2, s_{t-1} = 2 | y_t)]^{-1} \end{bmatrix} \quad (41)$$

Where $p(s_t = 1 | s_{t-1} = 1)$ is taken from *transition matrix* while $p(y_t | s_t = 1)$ is taken from *conditional distribution* equation. The initial value used is $p(s_0 = 1 | y_0)$. With the same procedure we can also estimate the value of p_{22} . The initial values that we use to estimate the parameter are

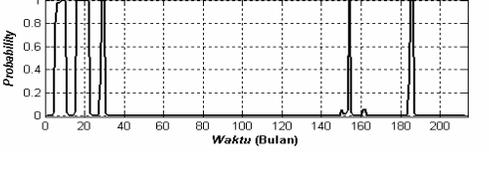
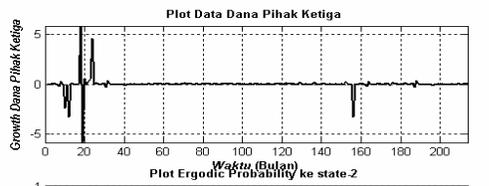
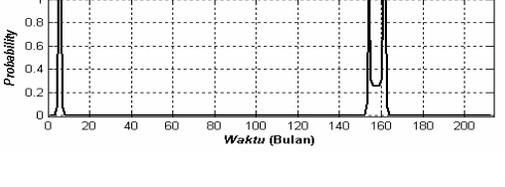
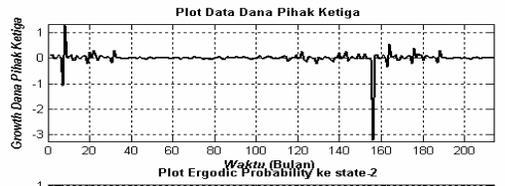
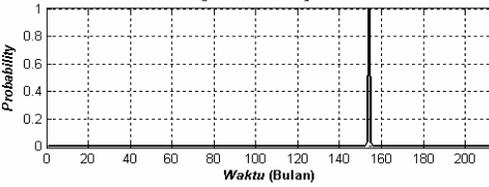
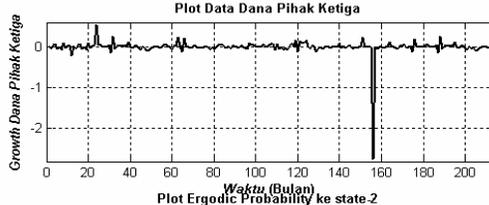
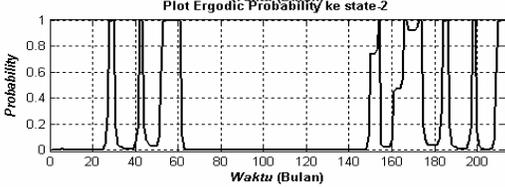
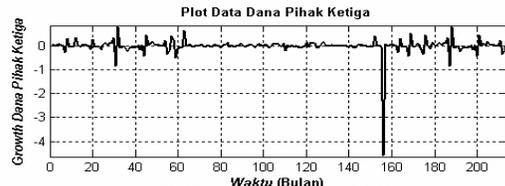
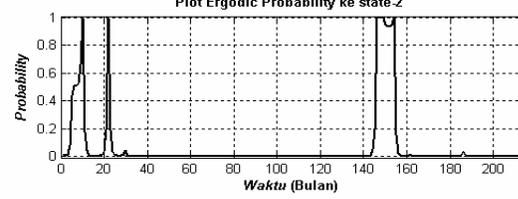
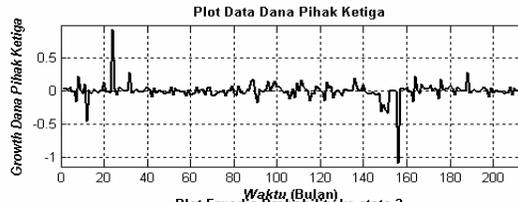
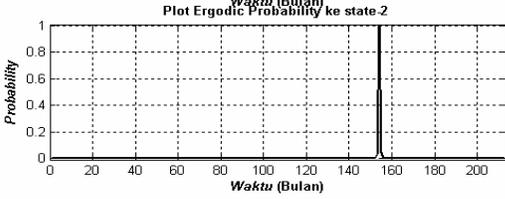
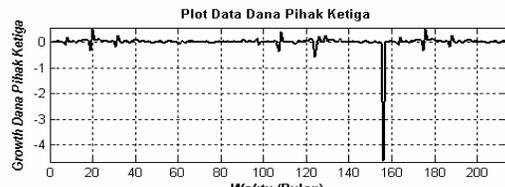
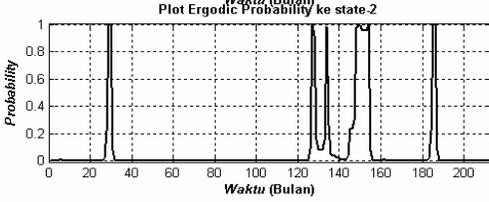
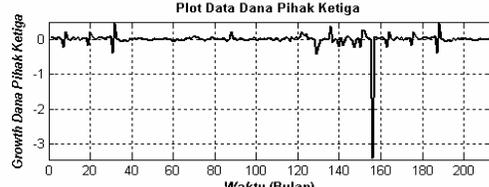
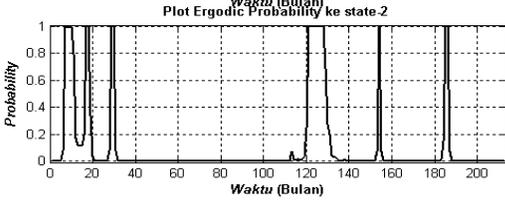
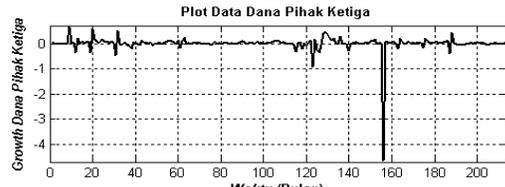
$$\{\alpha_1, \alpha_2, \phi_{1,1}, \phi_{2,1}, \phi_{3,1}, \phi_{1,2}, \phi_{2,2}, \phi_{3,2}, p_{11}, p_{22}, \rho_1, \rho_2, \sigma_1^2, \sigma_2^2\}$$

Plot Deposit Changes and Ergodic Probability To Bank Run State

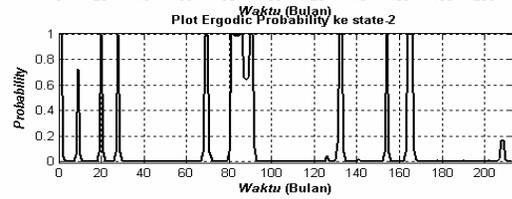
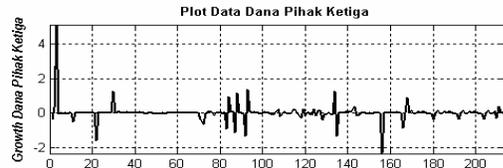
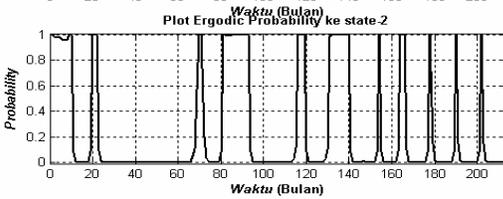
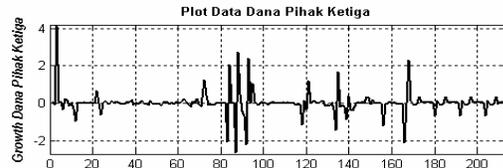
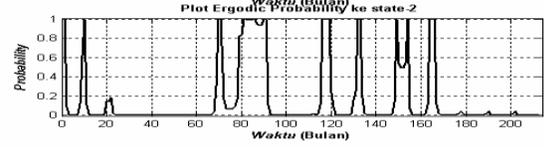
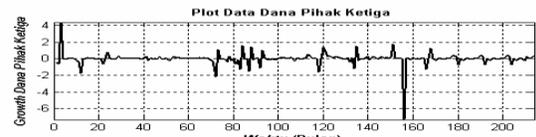
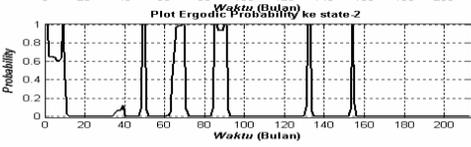
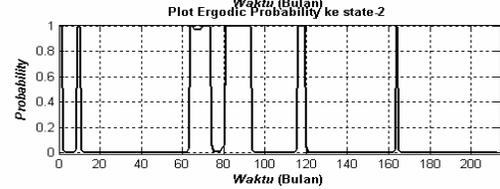
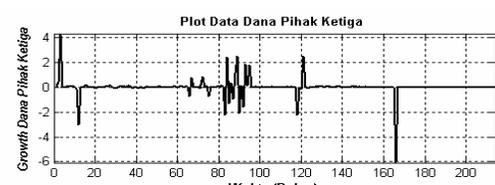
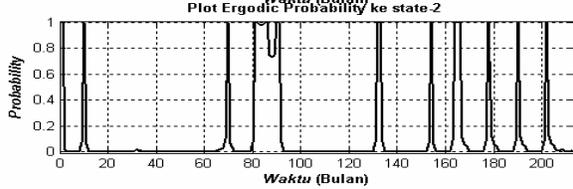
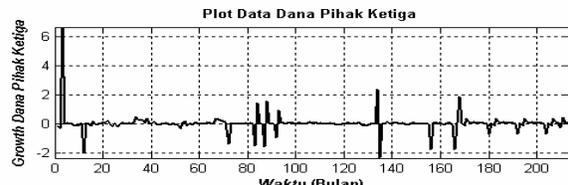
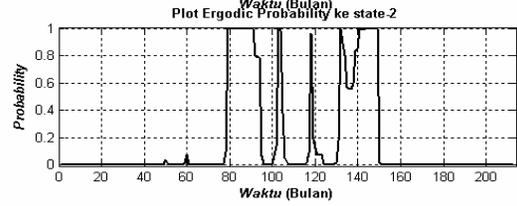
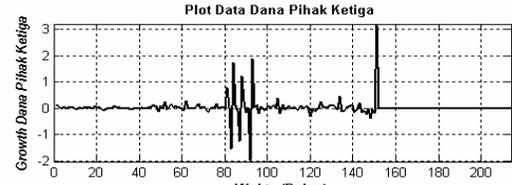
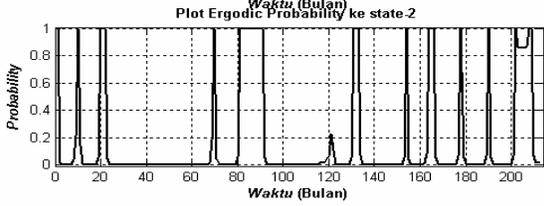
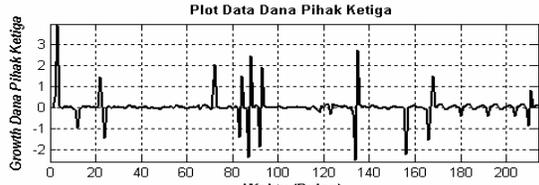
1. Stated-owned Banks (BP)



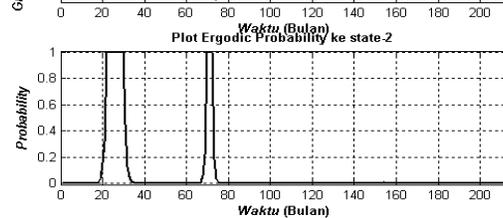
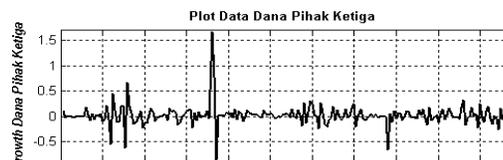
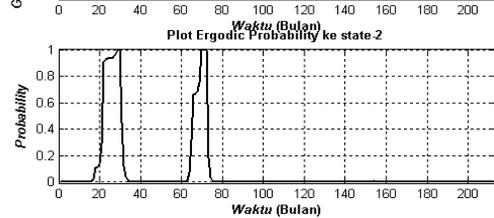
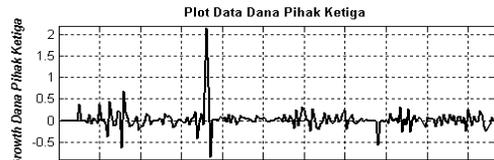
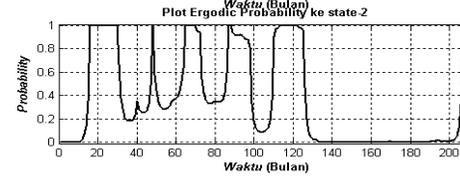
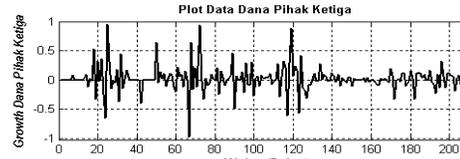
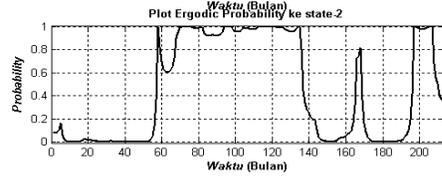
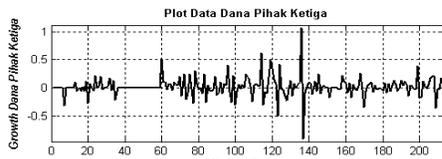
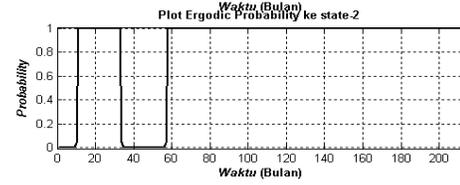
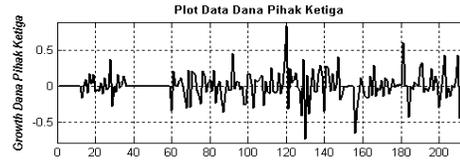
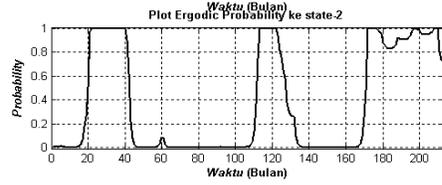
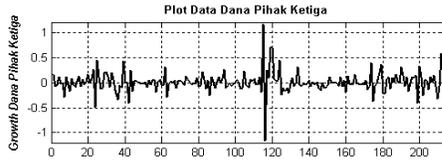
2. Private Foreign Exchange Banks (BSD)



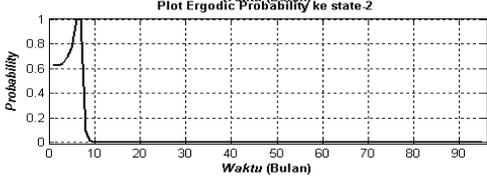
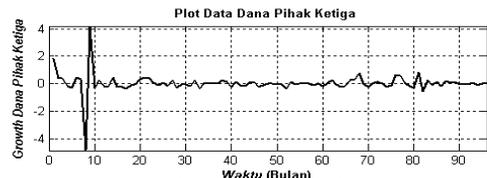
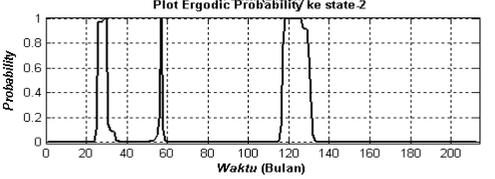
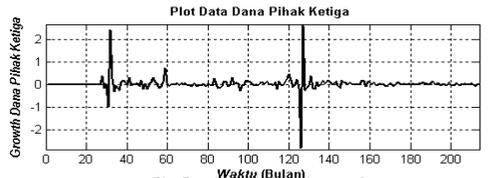
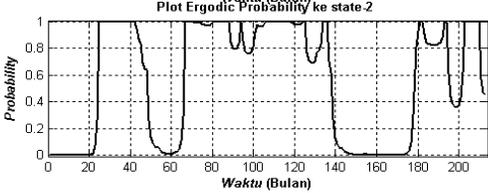
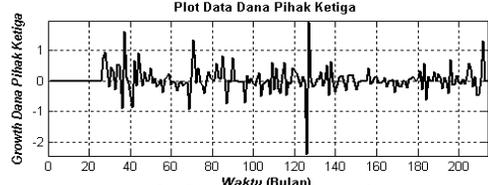
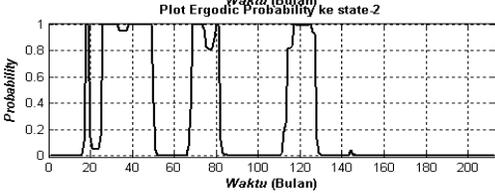
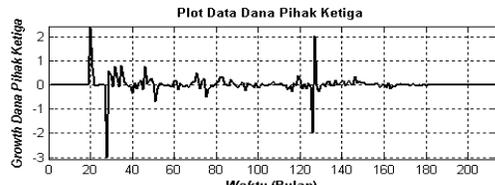
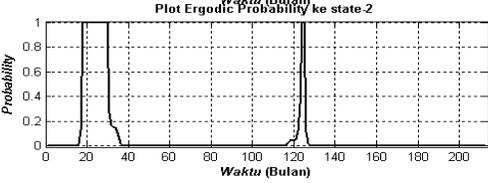
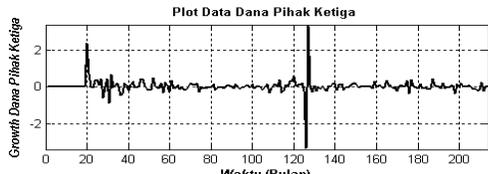
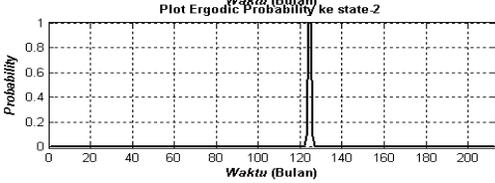
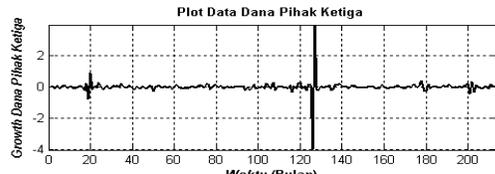
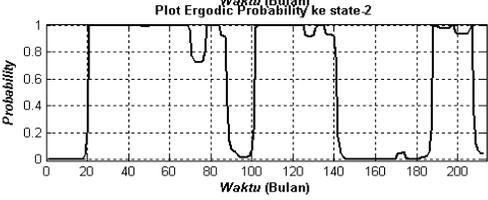
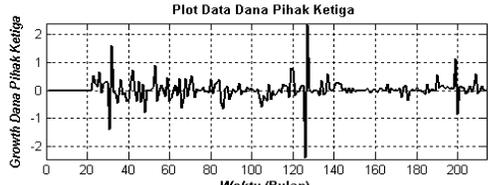
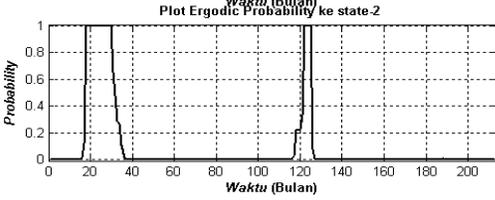
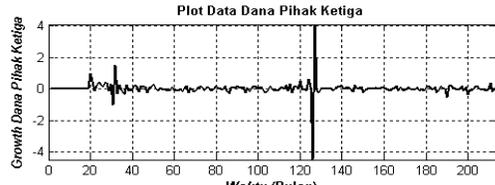
3. Private Non Foreign Exchange Bank (BSND)



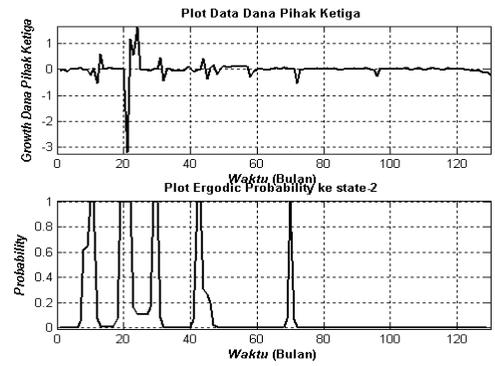
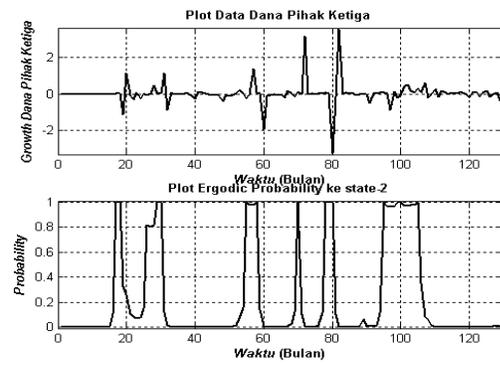
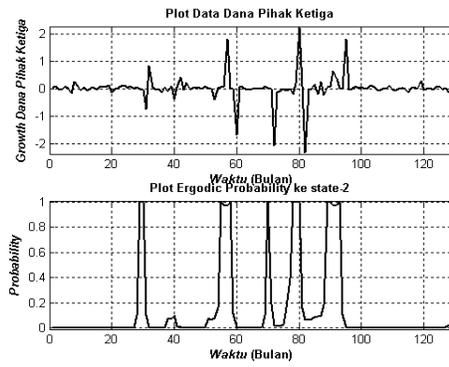
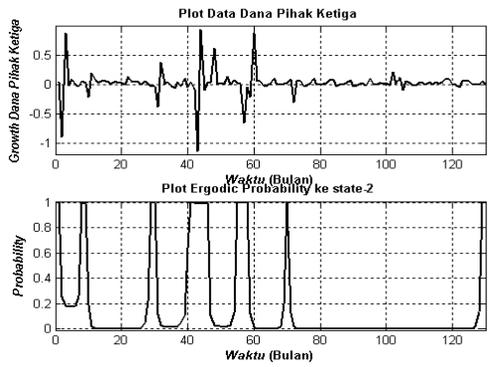
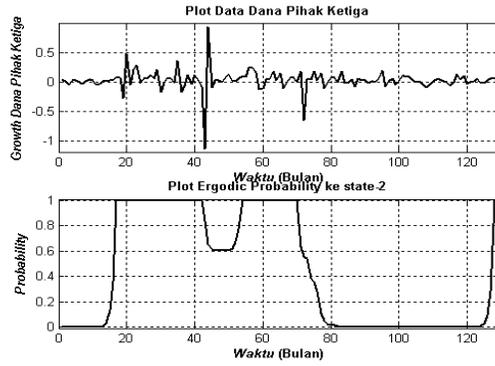
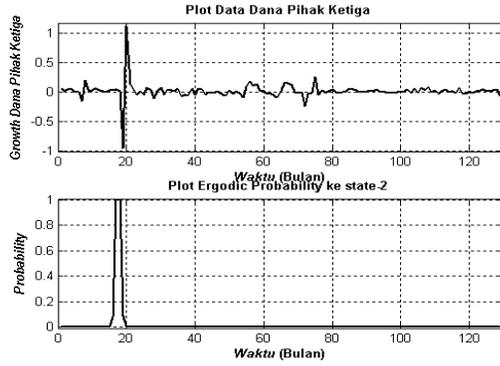
4. Foreign Banks (BA)



5. Joint Venture Banks (BC)



6. Banks with Frozen Activity (BBKU)



7. Banks with Frozen Operations (BBO)

