Time-Varying Threshold Regression Model Using the Kalman Filter Method

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Abstract : This paper explores a model, called the time-varying in threshold model with two regimes and which allows the regression coefficients to change over time. This model take the advantage of the Kalman filter allowing the parameters to vary over time. We apply our model to analyze the effect of bank credit on GDP growth and inflation because the financial time series data revealed strong signs of non-linearity and the context of the global economy has clearly changed in various dimensions. Note right away that the conventional threshold regression model appropriates when the relationship between dependent and independent variable seems constant, at least during the estimation period. Otherwise, a time-varying parameter non-linear model should be considered, especially in the context of structural change in the macroeconomics data. The main finding of this study reveals that there exists obvious important role the bank credit plays in the growth of the economy and inflation and there is a difference in behavior between regimes. However, after 2005 the effect from bank credit on GDP growth and inflation are quite smooth partly due to change in the monetary policy is called inflation targeting and reform the credit regulations of the commercial bank to more caution.

Keywords : Bayesian; Bayes factor; prior sensitivity analysis; time-varying; threshold regression model.
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1   Introduction

Over the last several years, the financial time series data revealed strong signs of non-linearity partly due to the volatility of the global economy and liberalization of capital flows. The context of the global economy has clearly changed in various dimensions. The "New Normal" will affect the global economy and it is hard to avoid. With liberalization of capital flows, bank credit has played even more important role in economic activities. In several times, bank credit appeared to be a major cause of economic crisis as well as a mechanism for helping economic recovery.

According to economic theory, there are two main roles bank credit can play for the advantage of the economy. First is the role in supporting sustainable economic growth as bank credit helps get funds back into the economic system through the credit market. Since saving is a leakage or fund outflow from the economy that means if saving increases, consumption will be decreased and then led to an economic downturn. Credit market, however, provides financial instruments that can bring back the outflow funds into the economy through loans. These include loans to the government, known as public loans by purchasing government bonds, and loans to the private sector for consumption or investment, known as private loans. As a result, we can control aggregate demand in the economy. Second is the role of bank credit in economic stability because inappropriate amount of credit in the market will cause economic volatility through inflation. For instance, if banks lend large amount of money in the economy, aggregate demand will increase to the extent of inflation or asset prices pressure. Consequently, this might lead to economic instability or market collapse. Therefore, for policymakers, it is very important to make decision wisely about the credit regulations taking into account all available data and past experience they have to make policy more effective. Moreover, the development in financial sector in recent years has grown more complicated for treatments by conventional economics as evident not only in the literature but also in reality.

There are several studies focusing on the theoretical models of economic growth and its relationship with credits. Biggs, Mayer, and Pick (2009) [1] argued that it was more relevant to investigate the relationship between the change in credit stock and GDP. They found that both new borrowing and credit impulse, which is the change in new credit issued as a percentage of GDP, were statistically significant in explaining quarterly GDP growth in US. Moreover, they showed that a rebound in economic activity was closely related to rebound in the credit impulse, i.e. bank credit rapidly grows in US recovery periods. Leitao (2012) [2] applied a dynamic panel data and GMM-system estimator to examine the link between bank lending and economic growth for European Union (EU-27 [2]). The results showed that the inflation and bank credit have a negative impact on economic growth. Ermisoglu,

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[2]27 member states of the European Union (EU). There are Sweden, Denmark, Ireland, United Kingdom, Netherlands, Finland, Cyprus, Luxembourg, Germany, Austria, Czech Republic, France, Portugal, Belgium, Italy, Estonia, Spain, Lithuania, Malta, Romania, Slovenia, Latvia, Bulgaria, Greece, Hungary,

Akeelik and Oduncu (2013) [3], by using OLS regression, found that credit impulse and new borrowing significantly explain the pattern of the Turkish GDP growth and they have significant contribution to forecasting it. Banu (2013) [4] used OLS regression to analyze the link between credit and economic growth in global crisis. He found that there is a strong connection between the credit granted to household and the GDP, as compared to the credit granted to public administration and the GDP.

The issue of the credit impact on economic growth is considerably more interesting to policymakers, financial institution and investors. This study, therefore, aims to examine the effect of bank credit on GDP growth and inflation. It focuses on the Thai economy because credit in Thailand varied over time in the past decades. Thailand experienced the economic crisis with the financial collapse in 1997, also well known as the Tom Yum Goong crisis. In other words, starting from 1994 credit in Thailand increased dramatically before plunged during the crisis in 1997. Then, in year 2000, credit volume started to recover and continued growing slightly until 2007. After that, government issued credit policy to encourage consumption among households in order to stimulate growth in the economy which suffered from global financial crisis. As a result, credit grew rapidly and became more volatile.

The time-varying threshold regression model is used in this study. The advantage of using this model resides in its ability to explain the behavior of credit in different regimes because time is the most important threshold variable. Moreover, the importance of each variable is allowed to change over time. Kalman filter is used in the prediction and updating the time varying coefficients thus the model could be able to adapt itself to the means and covariance of the input time series gradually. Furthermore, it can do so one-step at a time (Punales, 2011 [5]). Moreover, another advantage of this model is that it allows the response variable and explanatory variables to vary with time through smooth function. It is also able to capture the underlying temporal dynamics by allowing the regression coefficients to change smoothly over time. It has been studied by Hoover et al. (1998) [6], Wu et al. (1998) [7], Fan and Zhang (2000) [8], and Huang et al. (2002) [9] for longitudinal data where multiple realizations are available to the practitioners.

The contribution of this research is twofold: First, we introduce a new model, time varying threshold regression model to estimate the link between credit and economic indicators (GDP growth and inflation) of Thailand. Second, our contribution also is to show especially practitioners in financial area how to use time varying threshold regression models so that they can obtain more reliable conclusions from their data.

The remainder of this paper is organized as follows. In the next section, we describe the data. The third we explain the methodology regarding the time varying in threshold regression model and next section presents empirical study and results. The final section presents conclusions.

Slovakia, and Poland.

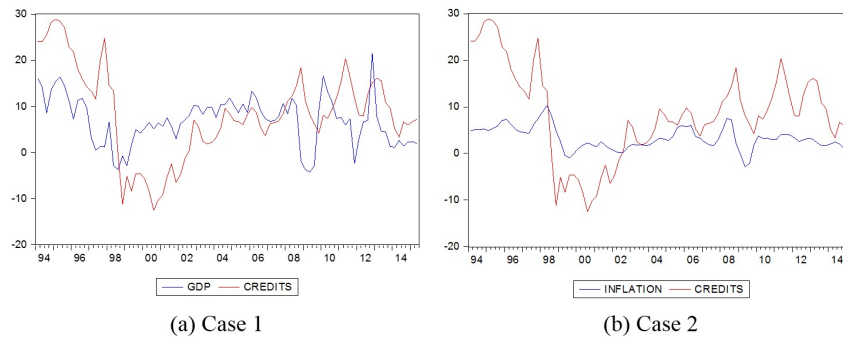(a) Case 1   (b) Case 2

Figure 1: Quarterly Commercial Bank Credit growth with Gross Domestic Demand growth and Inflation

2 The Data

In this paper, we use quarterly Thai GDP growth, inflation, and commercial bank credit growth from 1994 to 2014 to analyze the dependence between the studied variables. This period was chosen on the basis of its providing a sufficient number of observations for GDP growth, inflation and credit growth data. The data were obtained from the Office of National Economic and Social Development Board, Ministry of Commerce, and Bank of Thailand respectively. From Figure 1 we can find that bank credit growth data contain significant information for explaining the movement of GDP growth and inflation.

From Figure 1(a), it could be seen clearly that GDP growth and credit growth have moved in correlation with each other. Prior to the crisis in 1997, the high level of credit had stimulated the growth of GDP to the extremely high level. After the event the credit growth decreased because a lot of banks collapsed as well as the decline in GDP. It is long period for the economy to recover and for the growth to be positive. Figure 1 (b) shows the movement between inflation rate and credit growth. In 2000, Bank of Thailand announced the adoption of inflation targeting and Thailand has performed excellently in price stability ever since. However, there are signs of amplification of inflation rate during credit shock.

3 Methodology

3.1 Threshold Regression Model

The threshold model since introduced by Tong (1983) [10] has become popular in both statistics and econometrics. Particularly, it has many applications in economics, e.g., Potter (1995) [11], Girma (2005) [12], and Yu (2012) [13]. Consider the basic threshold regression model:

$$y_t = \alpha X_t + \varepsilon_{1,t} \qquad \text{if} \quad \delta_t \leq \omega \tag{3.1}$$

$$y_t = \beta X_t + \varepsilon_{2,t} \qquad \text{if} \quad \delta_t > \omega \qquad (3.2)$$

where α and β are the estimated coefficients, ω is referred to as threshold parameter and $\varepsilon_{1,t}$ and $\varepsilon_{2,t}$ are $n \times 1$ vector which is assumed to have normal distribution with zero mean and variance σ. The movement of the observations between the two regimes is governed by the variable δ_t, representing the regressor term (X_t). If δ_t is greater or lower than ω, the separated observations can be estimated as a linear regression. Thus, parameter δ_t is a crucial parameter in the model and we need to specify it or estimate it correctly. In the threshold regression model, Eq.(3.1) and Eq.(3.2) are separated into two regimes of the non-linear model as below or above the threshold parameter. For identification of regimes, we interpret the first regime as low growth regime and the second as high growth regime.

According to West and Harrison (1997) [14] and Shumway and Stoffer (2006) [15], time varying or state space models become far more flexible that they have been commonly used to model heterogeneous dynamics of data over time. The study of Fabozzi and Francis (1978) [16] and Bos and Newbold (1984) [17] revealed that the coefficient which depends on economic factors tends to be a time dependent one. Thus, this paper extends the time varying model to threshold regression and proposes a threshold regression with time varying coefficients. In addition, two regimes, consisting of high and low economic growth, are considered. Consequently, the threshold regression with time varying equation can be written as:

$$y_t = \alpha_t X_t + R\varepsilon_{1,t} \qquad \text{if} \quad \delta_t \leq \omega \qquad (3.3)$$

$$y_t = \beta_t X_t + M\varepsilon_{2,t} \qquad \text{if} \quad \delta_t > \omega \qquad (3.4)$$

where

$$\alpha_t = K_i \alpha_{t-1} + u_t \qquad \text{if} \quad \delta_t \leq \omega \qquad (3.5)$$

$$\beta_t = F_i \beta_{t-1} + v_t \qquad \text{if} \quad \delta_t > \omega \qquad (3.6)$$

where Eq.(3.3) and Eq.(3.4) are the observation equation while Eq.(3.5) and Eq.(3.6) are represented as a time varying equation whose "state" at time t are α_t and β_t. Since we take into account on the non-linear process in the time varying parameters, our paper aim to extend the linear AR(1) process to Threshold AR(1) process and construct the the non-linear time varying equation in Eq.(3.5) and Eq.(3.6). The fact that we consider TAR(1) process and not on previous states is an assumption of Markov assumption the future depends only on the present, and not the past, or put it differently given the present, the future and the past are independent. Thus, if we want to predict α_t and β_t we only need an estimate of α_{t-1} and β_{t-1} and measurement obtained at time t. The disturbance ε_t is observation errors in the threshold regression model; u_t and v_t are evolution errors and all assumed to be normally distributed, $N(0, \sigma_\varepsilon^2)$, $N(0, \sigma_u^2)$, and $N(0, \sigma_v^2)$, respectively. In addition, ε_t and u_t, v_t are assumed to be independent and not constant over time. Thus, if σ_v^2 and σ_u^2 are zero, the time varying equation does not exist. For the Matrices K_t and F_t are denoted as the coefficients of time varying equation for regime 1 and 2, respectively.

3.2   Posterior Estimation

The posterior estimation consists of the likelihood distribution and the prior distribution. For threshold regression model, the general form of posterior distribution is obtained by Bayes' rule. Let (Ω, A, P) be a probability space. Let $A_n, n \geq 1$, be a countable, measurable partition of Ω, and $B \in A$ be an event with $P(B) > 0$. Then, for many $n \geq 1$,

$$P(A_n \,|\, B) = \frac{P(B \,|\, A_n) P(A_n)}{\sum\limits_{j=1}^{\infty} P(B \,|\, A_j) P(A_j)}. \tag{3.7}$$

Indeed, we have

$$P(A_n \,|\, B) = \frac{P(A_n \cap B)}{P(B)} = \frac{P(B \,|\, A_n)\, P(A_n))}{P(B)}. \tag{3.8}$$

And writing

$$B = B \cap \Omega = B \cap (\cup_{j=1}^{\infty} A_j) = U_{j=1}^{\infty}(B \cap A_j). \tag{3.9}$$

We have

$$P(B) = \sum_{j=1}^{\infty} P(B \cap A_j) = \sum_{j=1}^{\infty} P(B \,|\, A_j) P(A_j). \tag{3.10}$$

It is easy to extend the above situation concerning events to discrete random variables. Let X, Y be discrete random variables. Then

$$P(X = x \,|\, Y = y) = \frac{P(Y = y \,|\, X = x) P(X = x)}{\sum_{x'} P(Y = y \,|\, X = x') P(X = x')} \tag{3.11}$$

which is the conditional density X of Y given . In this study, we can interpret $P(X > x)$ as prior distribution of X , then after observing $P(Y = y)$ or likelihood distribution, $P(X = x \,|\, Y = y)$ is the posterior distribution.

Prior to estimate the posterior distribution, first of all, the Kalman filter is conducted here as a statistic tool useful for estimating recursively unobserved and time-varying parameters or variables in econometric models. The algorithm of this method can be found in West and Harrison (1997) [14] and Shumway and Stoffer (2006) [15] and the algorithms are shown as the following:

1) Starting value at time t from the unconditional estimation.

Let $X_1 = [X \leq \omega]; X_2 = [X > \omega]$ thus,

$$\alpha_0 = (X_1' X_1)^{-1} X_1' y_1 \qquad \text{if} \quad \delta_t \leq \omega, \tag{3.12}$$

$$\beta_0 = (X_2' X_2)^{-1} X_2' y_2 \qquad \text{if} \quad \delta_t > \omega. \tag{3.13}$$

2) Prediction step.

Estimate the state vector α and β and their covariance matrix P_t at time t with information available at time $t - 1$, thus the prediction equation can be computed by

$$\left.\begin{array}{l} \alpha_{t|t-1} = c_{1t} + K\alpha_{t-1} \\ P_{1t|t-1} = KP_{1t-1}K' + R_t\sigma_\varepsilon R_t{}' \\ e_{1t} = y_{1t} - X_{1t}\alpha_{t|t-1} \\ f_{1t} = X_{1t}P_{1t|t-1}X'_{1t} + \sigma_{1u}^2 \end{array}\right\} \quad \text{if } \delta_t \leq \omega, \qquad (3.14)$$

$$\left.\begin{array}{l} \beta_{t|t-1} = c_{2t} + F\beta_{t-1} \\ P_{2t|t-1} = FP_{2t-1}F' + M_t\sigma_{2\varepsilon}M_t{}' \\ e_{2t} = y_{2t} - X_{2t}\beta_{t|t-1} \\ f_{2t} = X_{2t}P_{2t|t-1}X'_{2t} + \sigma_v^2 \end{array}\right\} \quad \text{if } \delta_t > \omega. \qquad (3.15)$$

3) Updating step

$$\left.\begin{array}{l} \alpha_t = \alpha_{t|t-1} - P_{1t|t-1}X_{1t}f_{1t}^{-1}e_{1t} \\ P_{1t} = P_{1t|t-1} - P_{1t|t-1}X_{1t}f_{1t}^{-1}X'_{1t}P_{1t|t-1} \end{array}\right\} \quad \text{if } \delta_t \leq \omega, \qquad (3.16)$$

$$\left.\begin{array}{l} \beta_t = \beta_{t|t-1} - P_{2t|t-1}X_{2t}f_{2t}^{-1}e_{2t} \\ P_{2t} = P_{2t|t-1} - P_{2t|t-1}X_{2t}f_{2t}^{-1}X'_{2t}P_{2t|t-1} \end{array}\right\} \quad \text{if } \delta_t > \omega. \qquad (3.17)$$

Repeat steps 2-3 for $t = 2, ...T$, we obtain the time varying coefficients for two regimes. Then, following Brigida (2015) [18], the log likelihood for the threshold regression can be formed as

$$L(\theta\,|Y,X\,) = \sum_{i=1}^{T}\left(\log(\frac{1}{2}\pi\,|f_1| + \left[\frac{1}{2}e'_1e_1f_1{}^{-1}\right])\right) +$$

$$+ \sum_{i=1}^{T}\left(\log(\frac{1}{2}\pi\,|f_2| + \left[\frac{1}{2}e'_2e_2f_2{}^{-1}\right])\right) \qquad (3.18)$$

where $\theta = \{K, F, \sigma_{1\varepsilon}^2, \sigma_{2\varepsilon}^2\sigma_u^2, \sigma_v^2, \omega\}$. To estimate the posterior distribution, we need to specify the prior distribution for the unknown parameter, θ. In this study, we choose the priors as follows. We take ω to be normal distribution with mean ω_0 and variance 0.01 and $\sigma^2 = \{\sigma_{1\varepsilon}^2, \sigma_{2\varepsilon}^2\sigma_u^2, \sigma_v^2\}$ is inverse gamma with scale $= \frac{v+n_1}{2}$ and rate $= \frac{v+n_1s_1^2}{2}$ for regime 1 and inverse gamma with scale $= \frac{v+n_2}{2}$ and rate $= \frac{v+n_2s_2^2}{2}$. Where v and s^2 are shape parameter and variance, respectively. For $\Theta = \{K, F\}$, the prior sensitivity analysis will be conducted and we will discuss the priors for these parameters in the next section. Thus, we can write the complete posterior distribution as

$$p(\Theta, \sigma^2, \omega\,|y, X\,) = L(\theta\,|y, X\,) + \Pr(\Theta, \omega, \sigma^2)_{\delta_t \leq \omega} + \Pr(\Theta, \omega, \sigma^2)_{\delta_t > \omega} \qquad (3.19)$$

To sample all of these parameters based on conditional posterior distribution, we employ the Markov chain Monte Carlo, Metropolis-Hastings algorithm (MH-algorithm), which is especially useful in extracting marginal distributions from full joint density function. The advantage of Metropolis-Hastings is that it will work well in the multivariate distribution and does not need an enveloping function (see, Lynch (2007) [19]).

A basic MH algorithm consists of the following steps:

1. Specify an initial value $\lambda_0 = \Theta_0, \sigma_0^2, \omega_0$.

2. Draw the candidate $\lambda^c = \Theta^c, \sigma^{2c}, \omega^c$ from the proposal function.

3. Compute the ratios

$$r = \frac{P(\lambda^c \,|y, X)p(\lambda_{i-1}\,|\lambda^c\,)}{p(\lambda_{i-1}\,|y, X)\ P(\lambda^c\,|\lambda_{i-1})}. \tag{3.20}$$

4. Compare r with random uniform [0,1] at each iteration draw. If $r >$ uniform [0,1], then $\lambda_j = \lambda_j^c$ otherwise, set $\lambda_j = \lambda_{j-1}$.

In this study, we run the MH sampler for 50,000 iterations where the first 20,000 iterations serve as a burn-in period.

4 Empirical Results

4.1 Model Specification

- <u>Case 1</u>

$$GDP_t = \alpha_t Credit_t + \varepsilon_{1,t} \qquad \text{if} \quad \delta_t \leq \omega \tag{4.1}$$

$$GDP_t = \beta_t Credit_t + \varepsilon_{2,t} \qquad \text{if} \quad \delta_t > \omega. \tag{4.2}$$

- <u>Case 2</u>

$$Inflation_t = \alpha_t Credit_t + \varepsilon_{1,t} \qquad \text{if} \quad \delta_t \leq \omega \tag{4.3}$$

$$Inflation_t = \beta_t Credit_t + \varepsilon_{2,t} \qquad \text{if} \quad \delta_t > \omega. \tag{4.4}$$

4.2 Unit Root Test

Prior to analyzing the time-varying threshold regression model, it is important to study the integration of variable order and ensure that all variables are stationary and integrated of the same order. In this paper, we used Bayes factor as a tool for test our data series. In this study, Unit-root testing based on Bayes Factor which introduced in Wang and Ghosh (2008) [20]. Consider the AR(1) process, $y_t = \alpha + \alpha_t y_{t-1}$, we switch notation of the null hypothesis $H_0 : \alpha_1 = 1$ to be the model M_0 and the switch notation of alternative hypothesis $H_1 : \alpha_t < 1$ to be M_1 the model. Thus, following the Bayes' Theorem, Bayes Factor can be written as,

$$BF = \frac{M_0(x)}{M_1(x)} \tag{4.5}$$

where $M_0(x)$ and $M_1(x)$ denotes the marginal likelihood of the data under model M_0 and M_1 . In the interpretation, Wang and Ghosh (2008) [20] suggested that the Bayesian unit-root test based on the Bayes Factor rejects the null hypothesis of stationary data if $BF < 1$.

The result in Table 1 provide summarize descriptive statistic and Bayes factor of data used in this study. The results show that the value of the Bayes factor is less than one that means all variables are stationary.

Table 1: Data description

	GDP	Credit	Inflation
Mean	3.2085	8.4229	6.8802
Median	2.9328	8.1062	7.3453
Maximum	10.2908	28.8876	21.5836
Minimum	-2.8236	-12.5399	-4.2191
Std. Dev.	2.4587	9.7396	5.2418
Skewness	0.2814	0.0167	-0.0962
Kurtosis	3.2180	2.7267	2.9432
BF	0.995	0.9963	0.9885
Observations	86	86	86

Source: Calculation

Then, the stability test, a cumulative sum of recursive residuals (CUSUM) test of Brown, Durbin, and Evans (1975) [21] is employed in this study to test the stability of the model. The results of the CUSUM test for two cases are plotted in Figure 2 and illustrate that the cumulative sum goes outside the area between the two 5% critical red dashed lines. The test clearly indicates instability in these two equations during our sample period. Thus, we can conclude that there exists a structural change in these equations and it is reasonable to employ the threshold model to model them.
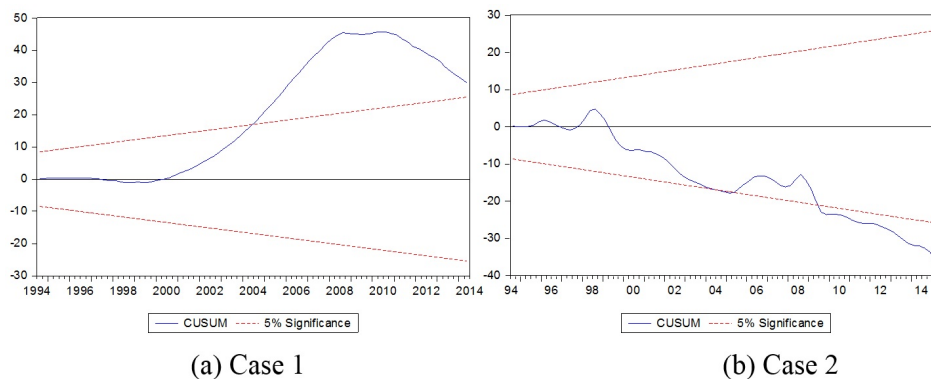

(a) Case 1   (b) Case 2

Figure 2: CUSUM Test

4.3   Prior Sensitivity Analysis

In the Bayesian estimation, the prior distribution plays an important role in the posterior distribution. If we do not specify the appropriate prior distribution, it will lead to the low accuracy of the posterior estimation (Stojanovski and Nur, 2011 [22]). As we mentioned in the previous section, we do not fix any prior on $\Theta = \{K, F\}$. A prior sensitivity analysis is conducted here to measure the robustness of results from the selection of prior distributions. In this study, we adopt five different priors consisting Normal, Normal-flat, Beta, Uniform, and Asymmetric Laplace distribution with different quantile levels. Table 2 provides a Deviance Information Criterion (DIC) and acceptance rate of any priors in two case studies. The results seem not more sensitive when the prior was changed. This indicates that the likelihood function dominates the posterior thus the change in any priors does not much affect the posterior estimation. We can say that our results will not be affected by different specifications of prior distribution. However, we found that the posterior with Normal-flat prior performed well in these two case studies since it provides the lowest DIC. In addition, the acceptance of the MH algorithm are 23.81% and 31.16% which present an optimal mixing in the posterior distribution for both cases.

Table 2: Prior sensitivity check

	DIC	Acceptance rate
Case 1		
Normal Prior	7196.281	22.49%
Normal-flat Prior	**7047.562**	23.81%
Beta Prior	7082.946	21.05%
Uniform Prior	7108.755	21.18%
ALD Prior α=0.25	7126.768	22.0.%
ALD Prior α=0.50	7118.731	21.05%
ALD Prior α=0.75	7126.322	19.82%
Case 2		
Normal Prior	7021.217	27.63%
Normal-flat Prior	**6904.899**	31.16%
Beta Prior	6954.639	28.79%
Uniform Prior	6926.128	31.87%
ALD Prior α=0.25	6941.011	32.16%
ALD Prior α=0.50	6940.354	31.45%
ALD Prior α=0.75	6943.282	31.55%

Source: Calculation

4.4   Parameter Estimates for Empirical Models

Table 3 shows estimated posterior mean of time-varying equations for 2 cases where Normal-flat distribution is conducted as the prior. In the first case, the results show a comparison of the posterior mean between high (Case 1-A) economic growth and low economic growth (Case 1-B) while the second case shows a comparison of the posterior mean between high level of inflation (Case 2-A) and low level of inflation (Case 2-B). The results show that the threshold parameter of GDP growth in Case 1 is equal to 8.101 and in Case 2 is equal to 8.092. As the value of the transition coefficient of time-varying (K_t) in Case 1-A is significantly negative, this means there is a change into opposite direction but not proportional for example if the coefficient in this quarter increases by one unit then the coefficient in the next quarter will decrease. While the transition coefficient of time-varying (F_t) in Case 2 is positive and significant that means if the coefficient in this quarter changes by one unit then the coefficient in the next quarter will change in the same direction. Therefore, it is observed that the behavior of the conditional variance is different between regimes. In Case 1, change in the coefficient that will take effect in the next quarter in regime 1 is greater than regime 2 and the second case is same with the first case.

Table 3: Posterior parameter estimations of time-varying regression model

Parameters	Case 1			Case 2		
	Mean	Std.	95% C.I.	Mean	Std.	95% C.I.
(A) Regime1: The data are lower than threshold value						
Sigma e	4.704	0.387	(3.778,5.398)	0.6567	0.337	(0.125,1.200)
Sigma u	0.718	0.242	(0.248,1.210)	0.327	0.053	(0.230,0.443)
Transition coefficient	-0.506	0.177	(-0.819,-0.149)	-0.402	0.086	(-0.538,-0.216)
Transition intercept	0.498	0.2447	(0.124,1.052)	0.216	0.092	(0.033,0.387)
(B) Regime2: The data are higher than threshold value						
Sigma e	5.245	0.592	(4.638,6.914)	1.685	0.310	(1.005,2.235)
Sigma v	0.168	0.051	(0.104,0.286)	0.128	0.020	(0.101,0.176)
Transition coefficient	-0.480	0.182	(-0.780,-0.103)	-0.384	0.104	(-0.567,-0.160)
Transition intercept	-0.699	0.1301	(0.452,0.923)	0.397	0.050	(0.299,0.494)
(C) Threshold parameter	8.101	0.032	(8.008,8.146)	8.092	0.049	(7.987,8.208)
D)Acceptance rate	21.05%			31.16%		

Source: Calculation

Figures 3 and 4 illustrate the marginal density plots, presented as the his-

togram of the parameters in the chain, where the x-axis represents the iteration of the algorithm, and the y-axis represents the simulated value of the estimated parameter at each particular iteration. Consider the convergence of this parameter set, there presents a good convergence behaviour and seems to converge to the normal distribution; thus we can get accurate posterior inference for parameters that appear to have good mixing.
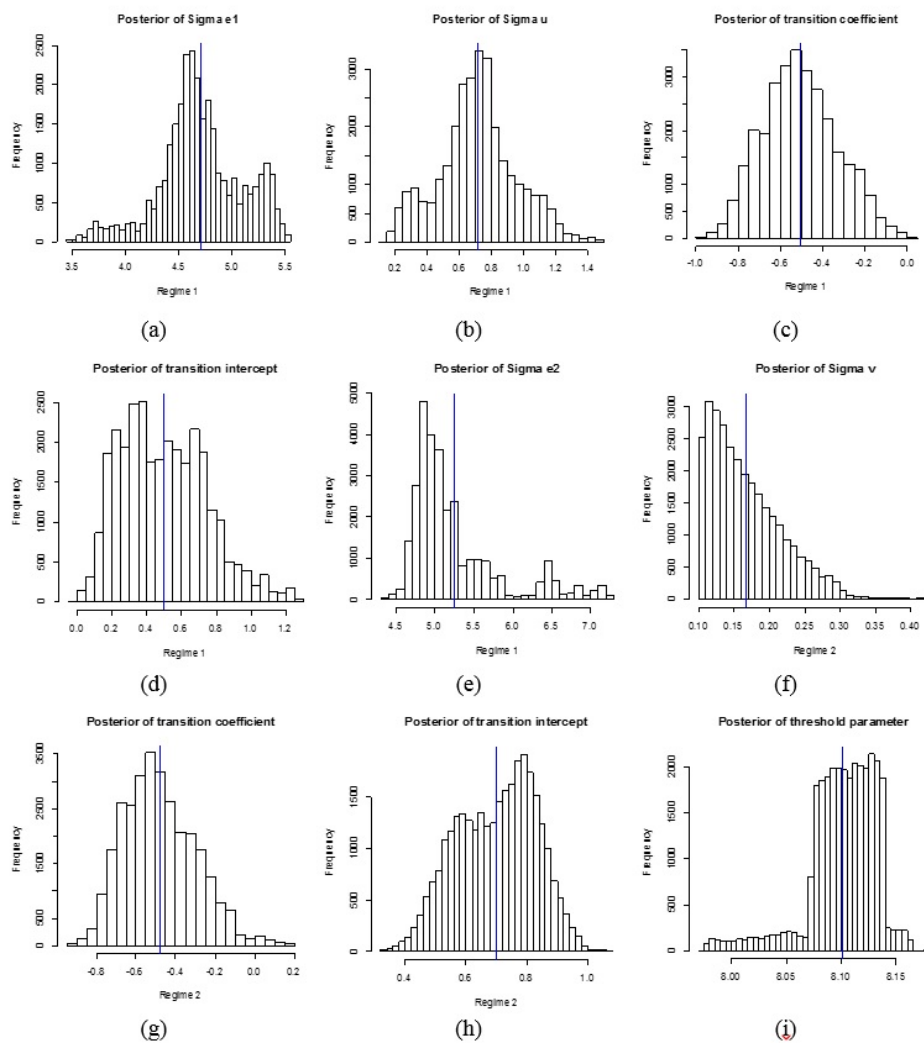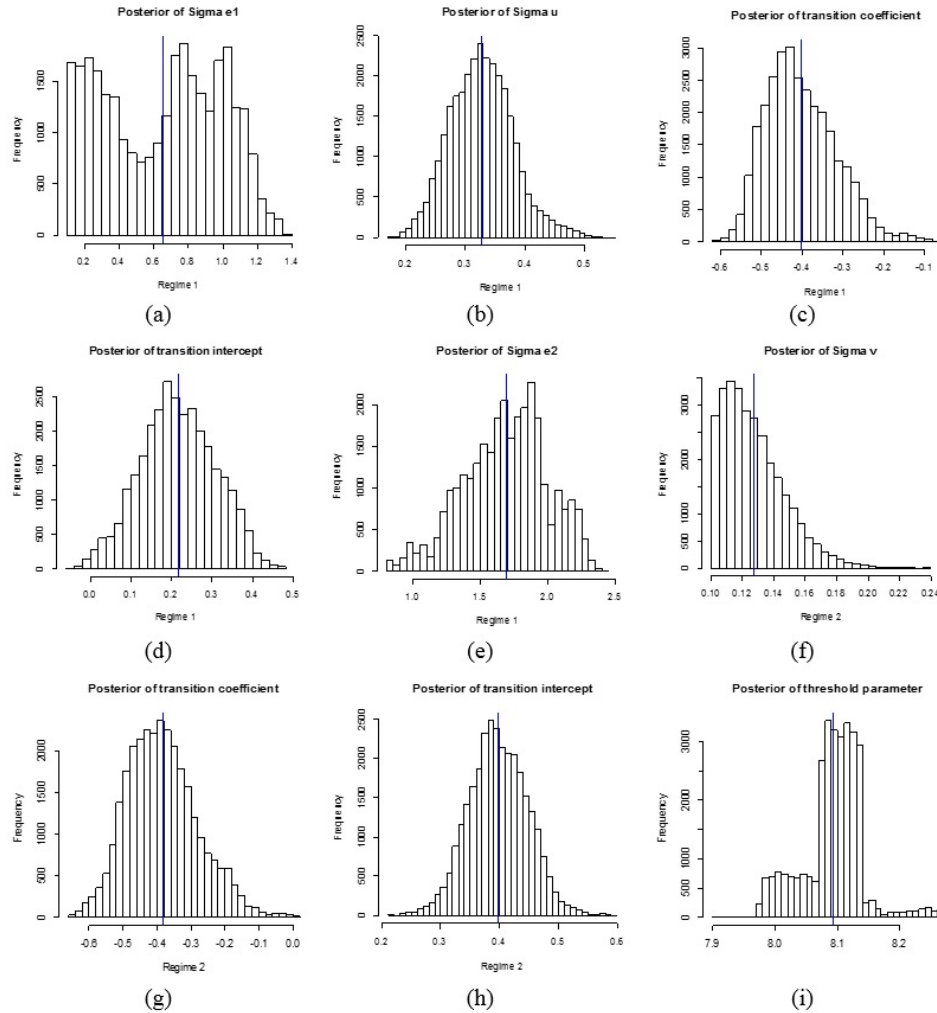

Figure 3: Parameter estimations of Case 1

Figure 4: Parameter estimations of Case 2

4.5   Economic Interpretation

Figure 5 presents the time-varying coefficient estimations of the bank credit effects on GDP growth (a) and inflation (b). In case 1, we found that the role of bank credit growth was very important to GDP growth both of before and after the economic crisis in 1997-1998. Before economic crisis, the rapid bank credit had stimulated aggregate demand. After that the lending activities of financial institutions were disrupted by the economic crisis. As a result, financial institu-

tions slowed down and limited credit approvals to reduce risks from the overall economic troubles. In five years later, financial institutions gradually resumed lending as liquidity in the system increased after slowing in the previous time. Moreover, the central bank did approve loans for key economic sectors in terms of relief loans at low interest rates or soft loan through financial institutions. This was intended to revive the economy experiencing a downturn after the economic crisis. Therefore, Thailand's economy returned to growth again after the economic crisis in 1997-1998. Since 2005, the coefficient of bank credit growth did not fluctuate much because the financial sector reform has continued in the process of economic development which was very important in preventing the next economic crisis. Around 2009-2010 the effect of bank credit on GDP growth has negative sign which means the increase of bank credit made GDP growth decline partly as a result of the domestic political instability which hampered the increased money in the economy to stimulate the economic growth.

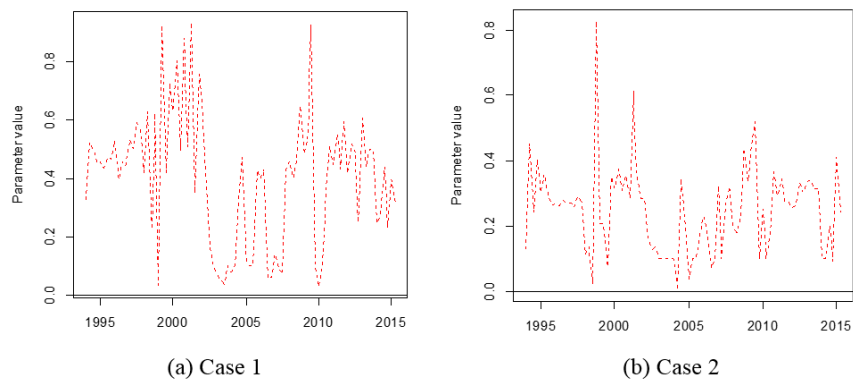(a) Case 1   (b) Case 2

Figure 5: Time-varying coefficient estimation

In addition to the above analysis, it can be suggested that not only did the bank credit play an important role in the economic growth but the change of money supply in the economy also affected inflation in that same period, as shown in case 2 of Figure 5. In 2000, Bank of Thailand announced the adoption of inflation targeting measure and Thailand has performed excellently in price stability ever since. This policy helps maintain the inflation movements within the framework of the policy. So the time-varying coefficients of case 2 are less than time-varying coefficients of case 1. This can be conclude that the impact of the bank credit on inflation is less than the impact of the bank credit on GDP.

5 Conclusions

The impact of bank credit on economic growth usually is measured using OLS regression or static model. However, the models are confined to the analysis of the

linear correlation, and can not reflect any time-varying characters and the different behavior between regimes. Therefore, the time-varying in threshold regression is appropriate to make up for the deficiencies.

This paper describes a model for analyzing the impact of bank credits on GDP growth and inflation in Thailand by the time-varying in threshold model, in which the empirical evidence shows that this method can be quite robust in estimating and forecasting non-linear correlation. The results reveal that bank credit can play an important role in the growth of the economy and the rise of inflation particularly in the economic recession. However, after 2005 the effects from bank credit on GDP growth and inflation are quite smooth compared to previously partly due to change in the monetary policy called "inflation targeting" and the reform of financial institutions after the crisis in 1997. According to our findings, we firstly would suggest that the authorities should closely monitor the movement of bank credit including bank credit policy carefully because it affects economic growth and inflation. Second, our analysis shows that bank credit flow measures are significant in explaining the GDP growth and inflation.

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