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Macroeconomic Factors Affecting Exchange Rate Fluctuation: Markov Switching Bayesian Quantile Approach

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Abstract : We employ Markov switching Bayesian Quantile regression (MSBQR) to investigate macroeconomic factors of exchange rate fluctuation in Thailand. The approach allows us to capture the effect of macroeconomic variables on the different levels of exchange rate and also accommodate structural breaks in exchange rate. The results show that the inflation rate has slight effect on the exchange rate, while the effect is greater in the case of the bond yield and public debt.

Keywords : exchange rate; economic growth; Thailand; Markov switching Quantile regression; Bayesian.
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1 Introduction

Thailand is an open economy that has to trade with other countries. Before Asian financial crisis, Thailand used fixed exchange rate system which imposes exchange rate fixed at some values or tied to a foreign currency. Such system had a great effect in short run, but it did not reflect the on-going economic conditions and it was one of the reasons that led to the financial crisis. As a result, the Bank of Thailand had to change the fixed exchange rate system to the managed float one in which currencies are traded subject to the forces of supply and demand [1].

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Figure 1: The exchange rate fluctuation in Thailand January 2005-May 2015 (Unit: Thai baht per US dollar)

Figure 1 shows that the highest and lowest values of exchange rate are 41.7628 and 29.0765 during January 2005 - May 2015 in baht per US dollar. The primary reason why exchange rate fluctuation is interesting to economists is that the fluctuation may act as an impediment to international trade. Specifically, the fluctuation presents uncertainty about risk in trading process. Assuming the exporters and importers are likely to have risk-averse behavior the exchange rate fluctuation may affect any levels of international trade by undermining price and profit. Consequently, this affects the profit and welfare of producers and consumers [2]. In addition, the turbulent fluctuations of currency could encourage speculation in currency and impact the overall economy later on. Therefore, the Bank of Thailand has to intervene in the exchange rate fluctuation. It has to bear the loss of the greater burden of maintaining exchange rate.

The determinants of exchange rate fluctuation are of interest because of the exchange rates potential linkages to other economic variables [3]. Many studies including those by K. Aristotelous (2001) [4], M.D. McKenzie (1999) [5] and M. D. McKenzie and R.D. Brooks (1997) [2] have found this volatilitys significant effects on either imports or exports. The determinants of the exchange rate have to be concerned. Economic theory suggests that macroeconomic factors such as inflation, interest rate and government debt are important to explain the behavior of exchange rate.

There have been arguments that different levels of the exchange rate could be influenced by macroeconomic variables differently. To investigate such effects, the quantile regression method allows us to directly capture the impact of shocks at different magnitudes on the exchange rate [6]. However, many researchers have employed quantile regression that assumes a single structure for the conditional mean and variance. This study extended the estimation by relaxing the assumption of single regime in favor of a regime-switching model for the reason that the linear quantile models cannot accommodate the inclusion of some facts such as macroeconomic structural breaks. W. Ye et al. (2016) [7] proposed a Markov regime-switching quantile regression model for use with data likely to have equilibria jumps. Thus, this approach allows the coefficients in the model to be different for each regime and quantile. Moreover, the study applied Bayesian inference for quantile regression using a likelihood function based on the asymmetric Laplace distribution suggested by K. Yu and R.A. Moyeed (2001) [8] who also showed that using improper uniform priors for the unknown model parameters can yield a proper joint posterior. The Bayesian approach has many advantages over classical method including providing the entire posterior distribution of the parameters of interest, allowing for parameters uncertainty when making predictions, and flexible handling of complex model situations [9].

Therefore, we extend the recent literature by incorporating the advantages of Bayesian approach in the estimation framework. The Markov Switching Bayesian Quantile regression (MSBQR) is employed in this study to estimate the coefficients for each regime and quantile which can reflect the current economic conditions. The results of this study will be useful because the government will have more details in its consideration regarding policy for stabilization of the exchange rate.

The organization of this paper is as follows: Section 2 describes the scope of the data used in this study. Section 3 provides the methodology. Section 4 provides the estimation of this study. Section 5 discusses the empirical results. Conclusion of this study is drawn in Section 6.

2 Data Analysis

There are four variables of interest including Thailands exchange rate (EX) that is measured as Thai baht per US dollar (i.e. high exchange rate means baht depreciation), inflation rate (INF), bond yield (BY), and public debt (PD) collected from January/2005 to May/2015. The data were obtained from the Bank of Thailand. All series are transformed into the growth rate before starting estimation.

2.1 Summary Statistics

We employed various descriptive statistics to specify the distributions of the exchange rate growth, the inflation rate, the growth rate of bond yield, and the growth rate of public debt as reported in Table 1. According to skewness and kurtosis, it is possible to conclude that the inflation rate, the growth rate of bond yield and the growth rate of public debt do not fit well with normal distribution except the growth rate of exchange rate. On the other hand, the growth rate of bond yield and the growth rate of public debt exhibit positive skewness, indicating the right-tail distribution, while the inflation rate has negative skewness, meaning that the distribution has a left tail.

Table 1: Descriptive Statistics of Macroeconomic variables.

Statistics	EXG	INF	BYG	PDG
Mean	-0.0011	2.8782	-0.0022	0.0051
Median	-0.0023	2.9779	-0.0105	0.0038
Maximum	0.0354	9.1732	0.1802	0.0818
Minimum	-0.0355	-4.3905	-0.2718	-0.0678
Standard deviation	0.0138	2.2220	0.0669	0.0170
Skewness	0.0976	-0.3648	0.0654	0.1431
Kurtosis	3.1904	4.4913	4.7691	8.0471
First quantile	-0.0091	1.9362	-0.0447	-0.0029
Third quantile	0.0081	3.9360	0.0402	0.0120
No. of observation	124	124	124	124

3 Methodology

There have been arguments that different levels of the dependent variable could be influenced by explanatory variables differently. Thus, we employ the quantile regression method to investigate such effect. However, we relax the assumption of single regime in favor of a regime-switching model in quantile regression for accommodate macroeconomic structural breaks. Therefore, we employ Markov switching quantile regression. The details are described as in the following.

3.1 Quantile Regression with Asymmetric Laplace Distribution

The basic idea of quantile is to equally divide the population into several segments. This idea was applied into the regression and introduced later as the quantile regression by Koenker and Bassett (1978) [10]. The quantile regression model consists of a set of regression curves which differ across different quantiles, therefore it is able to explain the relationship between regressors and dependent variable at different points in the conditional distribution of the dependent variable, which in turn make this model widely used in econometrics [11].

The quantile function can be shown in the following equation in which y is a dependent variable assumed to be linearly dependent on x. The term $Q_y(\tau\,|x)$ is the τth quantile regression function of y given x and $F_y(b\,|x)$ is the conditional distribution function y of given x.

$$Q_y(\tau|\,x) = \inf\{\,b|\,F_y(b|\,x) \geq \tau\} = \sum_k \beta_k(\tau)x_k = x'\beta(\tau) \tag{3.1}$$

The coefficient $\beta(\tau)$ shown in eq.(3.1) determines a relationship between vector x and the τth conditional quantile function of y. The dependence is conditional if exogenous variables are included in x, and conversely; the dependence is unconditional if no exogenous variables are added into x [12]. The value of $\beta(\tau)$ for τ in $[0, 1]$ determines the complete dependence structure of y. From eq.(3.1) we can simply write down the quantile regression model as in the following form:

$$y_t = x_t'\beta(\tau) + \varepsilon_t(\tau), \ \ t = 1, ..., T \tag{3.2}$$

Form the above equation, the term y_t represents dependent variable and x_t represents a vector of independent variables. The error term, ε_t, has a distribution which depends on the τth quantile. Moreover, $\beta(\tau)$ illustrates a vector of unknown parameters which determines a relationship between vector x_t and the τth conditional quantile function of y_t. Thus, the coefficient $\beta(\tau)$ for a given τ , where $0 < \tau < 1$, can be estimated by minimizing the weighted absolute derivations between y_t and x_t [12] which are shown as follows:

$$\hat{\beta}(\tau) \ = \ \arg\min \sum_{t=1}^{n} \rho_\tau(y_i - x_t'\beta(\tau)) \tag{3.3}$$

Where $\rho_\tau(.)$ is eq.(3.4) and $\hat{\beta}(\tau)$ is the quantile regression estimate $\beta(\tau)$ at the τth quantile.

In the mean linear regression, the Ordinary least square (OLS) estimation is equivalent to the parametric setting where the error term is normally distributed from which asymptotic estimators of coefficients can be derived as they are Maximum likelihood estimator. Quantile estimation is equivalent to the parametric case where the error term is asymmetrically Laplace distributed (ALD). The minimization of the objective function eq.(3.3) and the maximum likelihood theory is provided by the ALD [13]. The ALD is a continuous probability distribution which is generalized from the Laplace distribution in which its probability density function is given by:

$$f(y \middle| \mu, \sigma, \tau) = \frac{\tau(1-\tau)}{\sigma} \exp\left\{ -\rho_\tau \left(\frac{y-\mu}{\sigma} \right) \right\} \tag{3.4}$$

where μ is location parameter, $\sigma > 0$ is scale parameter and $0 < \tau < 1$ is skew parameter. The $\varepsilon_t \sim ALD(0, \sigma, \tau)$ and *i.i.d.* in eq.(3.2) is assumed. The function ρ_τ is assumed to be the loss function which defined by $\rho_\tau(u) = u(\tau - I_{u<0})$, where I denote the usual indicator function. Due to the idea of $ALD(\mu, \sigma, \tau)$ and the τth quantile is equal to μ, the likelihood function of the quantile regression model using ALD for T observations is given as follows:

$$L(\beta_\tau, \sigma \middle| y) \ = \ \frac{\tau^T(1-\tau)^T}{\sigma^T} \exp\{-\sum_{t=1}^{T} \rho_\tau(\frac{y_t - x'_t\beta(\tau)}{\sigma})\} \tag{3.5}$$

where $y_t \sim ALD(x_t\beta(\tau), \sigma, \tau)$, $t = 1, ..., T$ which implies that the different quantile of y conditional on x have same slope and σ is considered as a nuisance parameter [8]. Therefore, the minimization of the objective function eq.(3.3) is equivalent to the maximization of a likelihood function eq.(3.5).

3.2 Markov Switching Quantile Regression with Asymmetric Laplace Distribution

We also incorporate the Markov switching approach into this quantile regression model for accommodate structural break in macroeconomic problems. The inference of the Markov switching quantile regression can be made through the Hamilton filter [14]. The main idea of the Markov switching is that there exists a switching in the model structure consisting of an intercept term, regression coefficients, and a covariance, where the switching is controlled by an unobserved variable s_t. The unobserved variable that is also called a stage or regime is governed by the first order Markov process with transition probability matrix P , which is defined by $p_{ij}(s_t = i\,|s_{t-1} = j)$, $i, j = 1, ..., N$, is illustrated by

$$P \;=\; \begin{bmatrix} p_{11} & p_{21} & \cdots & p_{N1} \\ p_{12} & p_{22} & \cdots & p_{N2} \\ \vdots & \vdots & \cdots & \vdots \\ p_{1N} & p_{2N} & \cdots & p_{NN} \end{bmatrix} \tag{3.6}$$

where p_{ij} is the probability that regime i is followed by regime j and the transition probability matrix P satisfies $\sum p_{ij} = 1$ [15]. Therefore, the Markov switching quantile regression (MSQR) model can be shown as

$$y_t = \beta_{s_t,0}(\tau) + \sum_{t=1}^{T} \beta_{s_t,t}(\tau) x_t + \varepsilon_{s_t,t}(\tau), \;\; t = 1, ..., T \tag{3.7}$$

The term s_t denotes the state variable where $s_t = 1, ..., k$. The intercept term and the regression coefficients are $\tau-$dependent and depend on the state variable s_t. In addition, the error term, $\varepsilon_{s_t,t}(\tau)$ is also $\tau-$dependent and depends on the state variable.

Let φ represent the unknown parameters, where $\varphi = (\beta_{s_t}(\tau), \sigma_{s_t}(\tau))$. The Markov switching with 2 regimes ($s_t = 1, 2$) are assumed for this study. Therefore, the sample conditional likelihood function of the MSQR model with 2 regimes for the τth conditional quantile function of y_t is given by

$$L(\varphi) = \prod_{t=1}^{T} \left[\sum_{s_t=1,2} p(y_t\,|x_t, \tau; \varphi, P) p(s_t\,|y_{t-1}, x_{t-1}, \tau; \varphi, P) \right] \tag{3.8}$$

Next, the maximum likelihood estimation (MLE) is employed to maximize this likelihood function eq.(3.8), and then the estimated parameters obtained from MLE will be used as an initial value for the Bayesian approach.

3.3 Bayesian MSQR

This study applied Bayesian inference for quantile regression. The Bayesian approach has many advantages over classical method including providing the entire posterior distribution of the parameters of interest, allowing for parameters uncertainty when making predictions, and flexible handling of complex model situations.

According to the Bayes theorem, the sample form of the posterior distribution of this model can be formed as

$$\Pr(\varphi, P, s_t \,|y_t, x_t) \propto \Pr(\varphi, P, s_t) L(\, y_t, x_t \,|\varphi, P, s_t) \tag{3.9}$$

From eq.(3.8), $L(y_t, x_t \,|\varphi, P, s_t)$ is the likelihood function of the MSQR model, where $\varphi = (\beta_{s_t}(\tau), \sigma_{s_t}(\tau))$. The rest of the function is the prior distribution $\Pr(\varphi, P, s_t)$, which can be formed as

$$\Pr(\varphi, P, s_t) = \Pr(\varphi) \Pr(P) \Pr(s_0 \left| \varphi, P) \prod_{t=1}^{T} \Pr(s_t \,|\varphi, P, s_{t-1}) \Pr(s_t) \right. \tag{3.10}$$

The Metropolis-Hastings (MH) sampler is employed to sample the initial parameters [16]. There are three parts in the prior distribution, where the first part is the unknown parameters (φ), where $\varphi = (\beta_{s_t}(\tau), \sigma_{s_t}(\tau))$, transition matrix ($P$) and the Markov process (s_t). We assume the prior distribution for the unknown parameters to be uninformative priors are adopted. The prior distribution for the transition matrix, P, is assumed to be Dirichlet. Thus, we have

$$\begin{aligned} &\beta_{s_t}(\tau) \sim N(0, \Sigma) \\ &\sigma_{s_t}(\tau) \sim IW(0.01, 0.01) \\ &P \sim \text{Dirichlet(q)} \end{aligned} \tag{3.11}$$

where Σ is the is a diagonal variance matrix parameter $\beta_{s_t}(\tau)$ and q is the vector of scale parameter. We select these three prior since the the sign of the $\beta_{s_t}(\tau)$ can be either positive or negative, the sign of $\sigma_{s_t}(\tau)$ must be positive and P should be persistence staying in their own regime. The MH iterations for φ process can be described as follows:

1. Starting at an initial parameter value, let $\theta^0 = \varphi^0$,P^0, and s_t^0,

2. Choosing a new parameter value close to the old value based on proposal function. The proposal distribution employed in the MH algorithm is a normal distribution with mean at the θ^0 and covariance (C_t), that is $\Pr(\cdot \left|\theta^0, .., \; \theta^{j-1}, C_t\right) = N(\theta^{(j-1)}, C_t)$. In MH algorithm, covariance of the proposal distribution,C_t, is set as $C_t = \sigma_d \operatorname{cov}(\theta^0, ..., \theta^{j-1}) + \sigma_d \varepsilon I_d$ after initial period, where σ_d is a parameter that depends on dimension d and ε is a constant term which is very tiny when compared with the size of the likelihood function.

3. Computing the acceptance probability which is calculated by

$$\vartheta_j = \frac{L(\theta^* \left|y_t, x_t\right) \Pr(\theta^{j-1}, C_t)}{L(\theta^{(j-1)} \left|y_t, x_t\right) \Pr(\theta^* \left|\theta^{j-1}\right., C_t)} \tag{3.12}$$

If $\vartheta_j \geq 1$ then draw trace $\theta^j = \theta^{j-1}$. If $\vartheta_j \leq 1$ then draw trace θ^j from a proposal distribution.

4. Repeat steps 2-3 for $j = 1, ..., n$ in order to obtain samples $\theta^1, ..., \theta^n$.

4 Estimation

The Model Specification

This paper considers the switching in Thailands exchange rate, so we propose the Markov Switching Bayesian Quantile Regression (MSBQR) model as an alternative tool to work on our interest. Thus, our specification model can be specified as follows:

$$EXG_t = \beta_{s_t,0}(\tau) + \beta_{s_t,1}(\tau)INF_t + \beta_{s_t,2}(\tau)BYG_t + \beta_{s_t,3}(\tau)PDG_t + \varepsilon_{s_t,t}(\tau) \quad (4.1)$$

In this study, we assume 2 regimes for the MSBQR model consisting of the high growth regime ($s_t = 1$) and the low growth regime ($s_t = 2$). The model is also applied at different quantile levels, $\tau = \{0.25, 0.5, 0.75\}$. To estimate the unknown parameters, we begin with estimating the MSQR model through the likelihood function eq.(3.8) using MLE to obtain the initial parameters (φ^0) for the Bayesian approach. For the initial value of transition matrix (P^0), we specify it as $\begin{bmatrix} 0.8 & 0.2 \\ 0.2 & 0.8 \end{bmatrix}$. Then, we determine the number of iteration as 20,000 iterations in order to fit our initial MSQR model. The unknown parameters are estimated from filtering the observed process for y_t and x_t to find the $\Pr(s_t \,| y_{t-1}, x_{t-1}, \varphi, P)$ as proposed in Sims, Waggoner and Zha (2008) [15]. Moreover, to derive the filter probability in MSQR model, the dynamic of transition probability, which controls the probabilities of switching between the regimes is computed using Hamilton filter. To estimate the model using the Bayesian approach, we use the initial values obtained from the MSQR model estimated by MLE. Then, we draw those parameters using the MH sampling for 20,000 rounds and discard 10,000 rounds as a burn-in. Finally, the density plots are taken into account to confirm that the distributions of the unknown parameters are converging to the normal distribution.

5 Empirical Results

The results can be divided into two parts. The first part is the summary statistics and the second part is on macroeconomic determinants of exchange rate fluctuation in Thailand using the Markov Switching Bayesian Quantile.

5.1 The Markov Switching at Each Quantile Levels Results

Figures 2-4 show that during 2008, the exchange rate decreased at any levels of quantile except quantile 0.75. With the economic downturn in US, people had no confidence to consume, and it led to the subprime crisis which caused the US dollar to depreciate continuously.

Figure 2: Markov switching at quantile 0.25

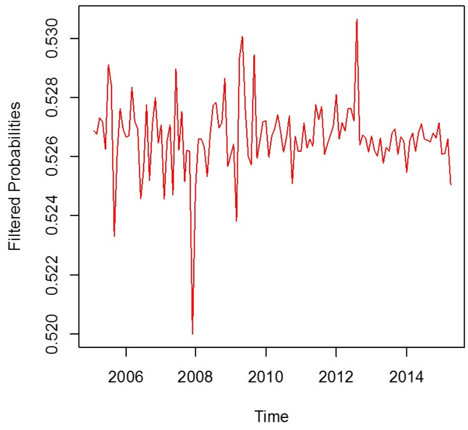


Figure 3: Markov switching at quantile 0.50

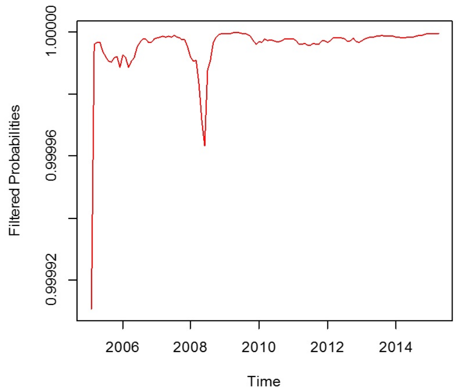
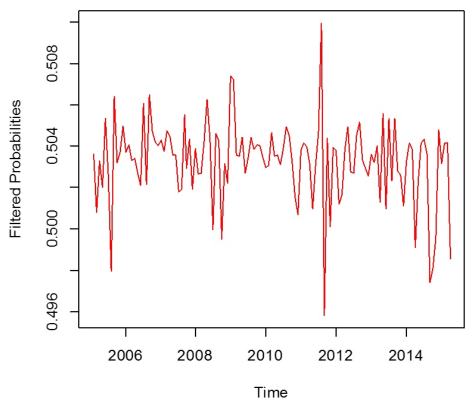


Figure 4: Markov switching at quantile 0.75



The central bank of the United States (FED) used Quantitative Easing (QE) policy to stimulate the economy. The impacts of QE on Thailand are that the US depreciation and the yield of US treasury declined which attracted the foreign capital inflow into the stock market and bond market in Thailand. Moreover, in 2012 the exchange rate decreased at quantile 0.75. After the European Debt crisis in 2012, many investors confidences in European financial market were greatly declined, shifting their interests to invest in Asian countries, including Thailand. As the result, the demand for Thai baht increased, causing the currency to be appreciated.

Table 2: The Estimates of transition matrix

	Transition Matrix		
Regime/Quantile	0.25	0.5	0.75
P11	0.49298	0.992893	0.474683
P12	0.50702	0.007107	0.525317
P21	0.493459	0.007445	0.531748
P22	0.506541	0.992555	0.468252
Duration			
Regime1	1.97231	140.7052	1.903612
Regime2	2.026513	134.3271	1.880591

Note: Regime 1 and regime 2 represent high and low exchange rate growth respectively

Table 2 shows the transition probability matrix is estimated by our model. At quantiles 0.25 and 0.75, the growth rate of exchange rate did not stay persistently in regime 1 and regime 2 because the probability of staying in regime 1 and regime 2 is about 50 percent whereas the probability of moving between these regimes is also almost 50 percent, indicating that many events can switch the series from regime 1 to re-gime 2. Unlike at quantile 0.5, the probability of remaining in either regime 1 or regime 2 is almost 99 percent, and a duration of being in each regime is persistent. However, we also found that there is little chance that the growth rate of exchange rate switches between these two regimes. This indicates that only an extreme event can switch the series to change from regime 1 to regime 2 and vice versa. Thus, the estimation of transition matrix provided the results that the growth rate of exchange rate at quantile 0.25 and 0.75, except quantile 0.5, have high fluctuation since the duration of each regime corresponds to a short period of time.

5.2 The Markov Switching Bayesian Quantile Regression (MSBQR) Results

The results of MSBQR are shown in Tables 3 and 4 and the plots of the point estimators with different regimes and quantiles with the range of quantiles from

0.1-0.9 are shown in Figures 5 and 6.

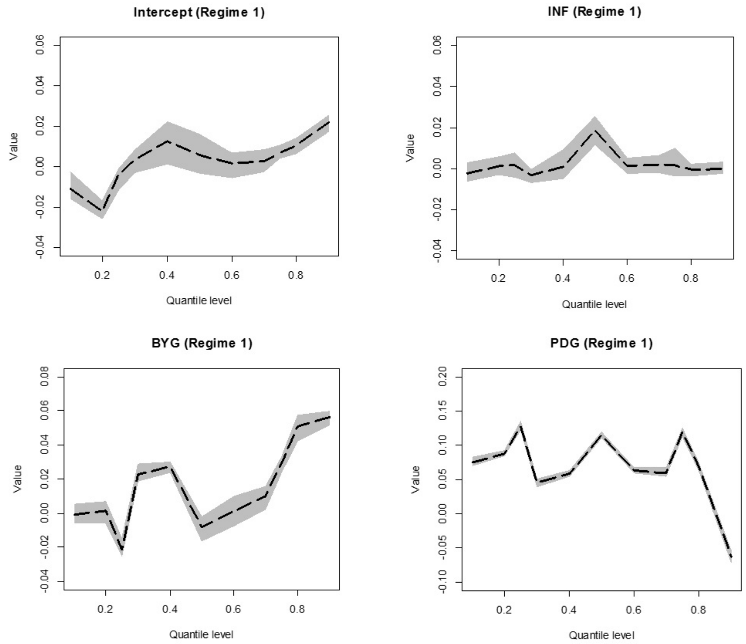
Table 3: The estimates from MSBQR in Regime 1 (High exchange rate growth)

Quantile	Coeff.	SE	2.5th	97.5th
Intercept				
0.25	-0.004	0.0026	-0.0116	-0.0009
0.50	0.0059	0.0056	-0.0032	0.0161
0.75	0.0068	0.0017	0.0043	0.0107
Inflation rate				
0.25	0.0015	0.003	-0.0041	0.0078
0.50	0.0186	0.0043	0.0115	0.0254
0.75	0.0014	0.0036	-0.0034	0.0099
The growth rate of bond yield				
0.25	-0.0215	0.0029	-0.0253	-0.0149
0.50	-0.0082	0.0043	-0.0165	-0.0022
0.75	0.0291	0.0027	0.0237	0.0332
The growth rate of public debt				
0.25	0.1281	0.0038	0.1219	0.1354
0.50	0.1147	0.0023	0.1106	0.1192
0.75	0.1197	0.0031	0.1123	0.1250

Table 3 and Figure 5 show change in coefficients due to the change in quantile level for each variable in regime 1. The coefficient of inflation rate is quite stable with moderate impact. The coefficient of inflation rate are 0.0015, 0.0186, and 0.0014 indicating that when the inflation rate increases 1%, the growth rate of exchange rate will increase by 0.0015%, 0.0186%, and 0.0014% at quantile 0.25, 0.50, and 0.75. Furthermore, it is possible to conclude that the change in inflation rate has only slight impact on the change in exchange rate growth due to the fact that the exchange rate is managed float. During the time of high inflation rate, the exchange rate may have already been close to the highest possible level set by the Bank of Thailand, making it less likely to have a fluctuation.

The coefficient of the bond yield variable in the quantile regression is increasing function of quantile. Stating with quantile 0.25 and 0.50, the growth rate of bond yield with coefficient of -0.0215 and -0.0082 indi-cates that when the growth rate of bond yield increases 1%, the growth rate of exchange rate will decrease by -0.0215% and -0.0082% in regime 1 respectively. The growth rate of bond yield has coefficients of 0.0291 at quantile 0.75, indicating that when the growth rate of bond yield increases by 1%, the growth rate of exchange rate will rise by 0.0291%. The higher growth rate of exchange rate reflects the fact that the ex-change rate fluctuates dramatically. Hence, at quantile of 0.25 and 0.5, the

Figure 5: Plots of the point estimators with different quantiles in regime 1 (High exchange rate growth)



negative coefficients of the bond yield can be concluded that the higher bond yield attracts foreign investors, resulting in the higher de-mand for Thai baht and causing it to appreciate. However, when the currency depreciates at the higher rate (i.e., at 0.75 quantile), the increase in bond yield growth causes the currency to depreciate even more. This may be because that the investors lose confident to invest in government bond. Even though the return of the government bond may be higher, but the fact that the currency depreciating at the faster rate does not seems to worth the effort. Therefore, the demand in Thai bath deceases and, as the result, the currency is depreciated.

Moreover, the coefficient of the public debt is fluctuating within quan-tile of 0.1 to 0.7 approximately but sharply declines after quantile 0.8. The growth rate of public debt with the coefficients of 0.1281, 0.1147 and 0.1197 implies the 1% increase in the growth rate of public debt will raise the growth rate of exchange rate by 0.1281%, 0.1147%, and 0.1197% in regime 1 at quantile 0.25, 0.50, and 0.75 respectively. At quantile 0.9, public debt with negative effect indicates when the inflation rate increases, the growth rate of exchange rate will decrease. It is possible to conclude that the impact of public debt on the growth rate of exchange rate remains positive for the most levels of quantile and becomes lower at the high level of quantile because of the managed-float exchange rate scheme prevents the exchange rate to grow any higher.

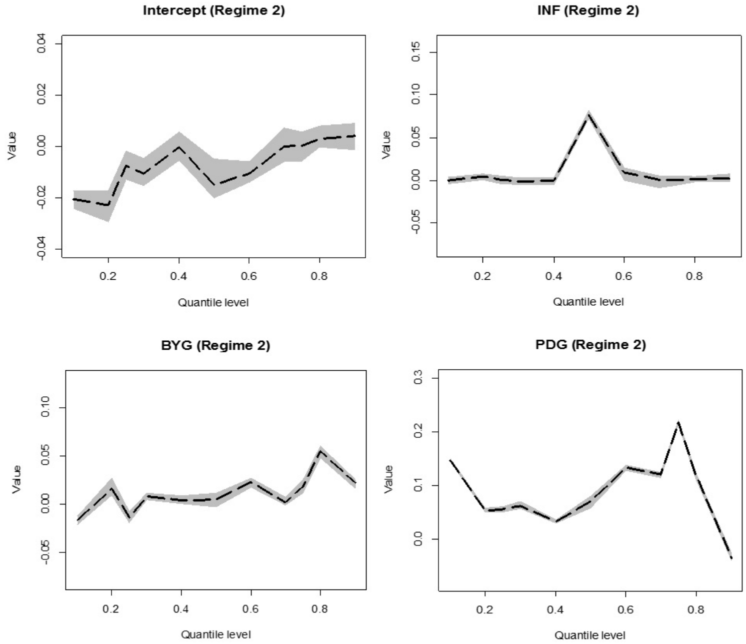
Table 4: The estimates from MSBQR in Regime 2 (Low exchange rate growth)

Quantile	Coeff.	SE	2.5th	97.5th
Intercept				
0.25	-0.0074	0.0032	-0.013	-0.0019
0.5	-0.015	0.0041	-0.02	-0.005
0.75	0.0003	0.0034	-0.0056	0.0056
Inflation rate				
0.25	0.0007	0.0026	-0.0042	0.0053
0.5	0.0765	0.0023	0.0726	0.0813
0.75	0.0006	0.003	-0.0053	0.0054
The growth rate of bond yield				
0.25	-0.0139	0.0032	-0.0189	-0.0075
0.5	0.005	0.0043	-0.0031	0.0111
0.75	0.018	0.0032	0.0117	0.025
The growth rate of public debt				
0.25	0.0565	0.0025	0.0509	0.0615
0.5	0.0709	0.006	0.059	0.0811
0.75	0.2178	0.002	0.2138	0.2213

Table 4 and Figure 6 show change in coefficient value due to the change in quantile level for each variable in regime 2. The coefficient of the inflation rate is quite stable with moderate impact. The coefficient of inflation rate is 0.0007, 0.0765, and 0.0006 in low regime indicating that when the inflation increases 1%, the growth rate of exchange rate will increase by 0.0007%, 0.0765%, and 0.0006% at quantile 0.25, 0.50 and 0.75 respectively. It is possible to conclude that the change in inflation rate has slight impact on the change in exchange rate growth just like in regime 1.

The coefficient of the bond yield variable in the quantile regression is quite stable but slightly increasing at the high levels of quantile. The growth rate of bond yield with coefficients of -0.0139 at quantile 0.25 indicates that when the growth rate of bond yield increases 1%, the growth rate of exchange rate will decrease by 0.0139% in regime 2. At quantile 0.5 and 0.75, the growth rate of bond yield with coefficients of 0.050 and 0.0180, indicating that when the growth rate of bond yield increases 1%, the growth rate of exchange rate will rise by 0.050% and 0.0180% respectively. The growth rate of bond yield is positively correlated with the growth rate of exchange rate in regime 2. It is possible to conclude that the higher growth rate of bond yield, the greater the im-pact it has on the growth rate of exchange rate. Then, the economic interpretation is the same as for regime 1.

Figure 6: Plots of the point estimators with different quantiles in regime 2 (Low exchange rate growth)



Moreover, the coefficient of the public debt is quite fluctuating but decreasing at the high levels of quantile. The growth rate of public debt with the coefficients of 0.0565, 0.0709, and 0.2178 implies the 1% in-creases in the growth rate of public debt will raise the growth rate of exchange rate by 0.0565%, 0.0709%, and 0.2178% in regime 2 at quantile 0.25, 0.50 and 0.75 respectively. At quantile 0.9, the growth rate of public debt in regime 2 with negative coefficient suggests that when the growth rate of public debt increases, the growth rate of exchange rate will decrease. It is possible to conclude that the impact of public debt on the growth rate of exchange rate remains positive for most levels of quantile and becomes lower at the high level of quantile and then the economic interpretation is the same as for regime 1.

6 Conclusion

This study investigates the macroeconomic factors affecting the ex-change rate fluctuation in Thailand using Markov Switching Bayesian Quantile regression during the period of January 2005 - May 2015. The study found that in the both regimes, the change in inflation rate has slight impact on the change in exchange rate growth. The growth rate of bond yield is positively correlated with the growth rate of exchange rate in both regimes. The effect of such change increases as the ex-change rate growth becomes higher. Moreover, the growth rate of public debt is also positively correlated with the growth rate of exchange rate in both regimes at any quantile except for the high quantile. The impact of public debt on the growth rate of exchange rate remains positive for most levels of quantile and becomes lower at the high level of quantile.

For regimewise, the effect of inflation rate and the growth rate of bond yield on the exchange rate growth are similar, while the effect of the growth rate of public debt is greater in the low regime than in the high regime.

To conclude, the inflation rate has slight effect on the growth rate of exchange rate, while the effect is greater in the case of the growth rate of bond yield and public debt. This implies that the government should put a great concern in controlling the proper level of bond yield and growth in public debt. An increase in these two factors, as the consequence of debt-financing fiscal policy, could exacerbate a depreciation of Thai Baht even further.

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