

**A New Approach to Combine Econometric Model with Time-series
Analyses-An Empirical Study of International Exchange Markets**

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Abstract

This paper uses the Markov-switching (MS) mechanism to create a composite model with an endogenous and non-constant loading on both of econometric model and time-series approach. The empirical data include the monthly U.S. dollar exchange rates of the currency of four industrialized countries including France, Germany, U.K. and Japan as well as two Asian developing countries including South Korea and Taiwan from 1980 to 2000. Our empirical findings are consistent with the following notions. First, the forecasting performances of the composite model with non-constant weight outperform each technique and random walk model in all cases. In contrast, the performances of the composite model with constant weight are unremarkable. Second, the state of low (high) volatility corresponds to the state of the forecasting technique of time-series approach (econometric model). Third, we denote the high volatility state of exchange markets of South Korea (industrialized countries) as a crisis (an unusual) condition. Moreover, the fundamental variables derived from economic theories would be invalid (valid) during the crisis state (unusual state) for South Korea (the industrialized countries).

Keywords: *exchange rate, ARMA, econometric model, Markov-switching model, Volatility*

JEL Code: *G15, F31, F37*

1. Introduction

Econometric model for generating exchange rate forecasts are based on fundamental analysis. They try to measure and quantify the relationships between exchange rates and a set of economic fundamentals. However, the difficulty in predicting the exchange rates has been a longstanding problem in international economics. In a highly influential paper, Meese and Rogoff (1983) note that the forecast performances of exchange rates produced by econometric models based on fundamentals are no better than those using random walk models. Even some recent studies have found some success at forecasting changes in exchange rates at longer horizons or using nonlinear methods (please refer to MacDonald and Taylor (1994), Chinn and Meese (1995), Mark (1995), Groen (2000), Mark and Sul (2001), Kilian and Taylor (2003)), however, the Meese-Rogoff results have not been convincingly overturned. Specifically, there are no strong evidences to prove any given econometric models/specifications as being very successful. In other words, one econometric model might do well for one exchange rate, but not for another.

Because of unremarkable prediction performances of econometric models based on fundamental variables, some econometricists propose time-series approaches to analyze the exchange rates. The ideas of time-series approaches are based their expectations of future changes of exchange rates solely on the past behaviors of

exchange rates, under the assumption that the lagged values of the change of the lagged exchange rates could be used to predict their future values. In other words, the time-series analysts do not believe in economic theories and assume that they are better off allowing the data to determine the models. Among various kinds of time-series models, ARMA (AutoRegressive Moving Average) model could serve as the representative. Review the prior studies which adopted the framework of ARMA model. Pong, Shackleton, Taylor and Xu (2004) used them to forecast currency volatilities. Aguirre and Saidi (2000) incorporate ARMA models with threshold model to test the asymmetries in exchange rates. Tschernig (1995) used them to examine the long memory behavior in exchange rates. Nijman, Palm and Wolff (1993) employed them to analyze risk premium in forward foreign exchange rates.

In this paper, we take a new line of attack on the questions of the link between econometric models and time-series approaches. In detail, this paper raises an interesting question: could we design a composite model that incorporated both of econometric models and time series techniques? The underlying idea is that the information from both of fundamental variables derived from economic theory and their own lagged variables should be valuable for market participants. Specifically, we believe that portfolio managers should weigh the information from fundamental variables from economic theories and the own lagged data. Moreover, in some periods,

we announce that managers would listen to the econometric models (time-series approach) with more (less) attention and vice versa.

Following the above line of thoughts, this paper establishes and examines a composite model from econometric models and time-series approaches on the exchange rates. Nevertheless, one of the main obstacles is the decision of weight on each of these two different forecasting techniques. In this paper, we employ the Markov Switching (MS) mechanism to decide the time-varying weight on various alternatives. In brief, we set up a framework with two states to capture two different forecasting alternatives. Moreover, one of features of MS model is to estimate the probabilities of specific state at each time point by data itself. In this paper, we use the estimated and time-varying probabilities to serve as the weight of each technique. Furthermore, one question we want to address and examine is: Do the composite models with time-varying loading outperform each of these two techniques and the random walk models?

Our work is related to the model in Engle and Hamilton (1990). They also employed the MS techniques and examine the long swing behaviors of exchange rates. However, there are several remarkable difference points in this paper. First, in contrast with them defining the setting with two states on the constant terms of regression equation, we establish and examine a framework with two states on the slop terms.

Second, Engle and Hamilton (1990) focus on discussing the nonlinearity of first moment for the quarterly exchange rates. We highlight the discussions of the second moments for the monthly data. By examining the realized percentage change in the exchange rates, we can find they are much more volatile during certain periods. The derivative question is: what are the relationships between the various volatility regimes and various forecasting techniques? Specifically, does the situation of high volatility regime correspond to the time-series approaches or econometric models?

Last but not the least, because of most of relative prior studies concentrating on analyzing the exchange rates of industrialized countries' currency, one of the features of our paper is that we are more interested in examining the exchange rates of developing countries' currencies and compare the differences between them.

The next section establishes our empirical models. In Section 3, we present our empirical results. In section 4, we provide several discussions and explanations for our empirical findings. Last, we conclude our paper in Section 5.

2. Model Specifications

(1) Time-series Approach

We adopt the ARMA (1, 1) to serve as a representative time-series approach. The ARMA (1, 1) setting is presented as following:

$$y_t = \alpha + \beta_1^T y_{t-1} + \beta_2^T u_{t-1} + u_t, \quad u_t \sim N(0, \sigma) \quad (1)$$

In the above setting, y_t and y_{t-1} are the percentage change in the exchange rate¹ in time t and time $t-1$, respectively. u_t and u_{t-1} are the residual term in time t and time $t-1$, respectively and follow the Gaussian distribution with standard error σ . Specifically, we use the β_1^T and β_2^T to capture the impacts of the one-period-ahead percentage change in the exchange rate (y_{t-1}) and its residual term (u_{t-1}) on the current percentage change in the exchange rate (y_t), respectively².

(2) Econometric Model

In this paper, we use two economic fundamentals, such as the inflation differentials (derived from Purchasing Power Parity) and the interest rate differentials (derived from Interest Rate Parity) to establish the following regression³:

$$y_t = \alpha + \beta_1^E (\pi_{t-1} - \pi_{t-1}^*) + \beta_2^E (r_{t-1} - r_{t-1}^*) + u_t, \quad u_t \sim N(0, \sigma) \quad (2)$$

In the above setting, π_{t-1} and π_{t-1}^* (r_{t-1} and r_{t-1}^*) present the inflation rates (interest

¹ We adopt the percentage changes in the exchange rates instead of the exchange rates to achieve stationarity. The Dickey-Fuller test (not reported here) shows that all of the data series adopted in this paper reject the null hypothesis of unit root.

² Surely for each country we can find and use the best ARMA model. However, in this paper, we do not target on finding the best ARMA model. In brief, the adoption of simple ARMA (1, 1) in this paper is acceptable for convenience.

³ There are some other fundamental variables to explain the exchange rates, such as relative money supplies and relative real income as well as relative account balances. However, the target of this paper is not to find the best econometric model for the exchange rates. Therefore, for the reasons of convenience, we only adopt two fundamental variables to establish the econometric model.

rates) of home and foreign countries in time $t-1$, respectively. u_t is the residual term in time t and follows the Gaussian distribution with standard error σ . Specifically, we use the β_1^E and β_2^E to capture the impacts of one-period-ahead inflation differentials ($\pi_{t-1} - \pi_{t-1}^*$) and interest differentials ($r_{t-1} - r_{t-1}^*$) on the current percentage change in the exchange rate (y_t), respectively.

(3) Composite Models

For capturing both the information from the fundamental variables and the lagged percentage changes in the exchange rates, we create the following two kinds of composite models.

(a) Composite Model with Constant Weight

$$y_t = \alpha + \beta_1^E (\pi_{t-1} - \pi_{t-1}^*) + \beta_2^E (r_{t-1} - r_{t-1}^*) + \beta_1^T y_{t-1} + \beta_2^T u_{t-1} + u_t, \quad (3)$$

$$u_t \sim N(0, \sigma)$$

Intuitively, the above regression considers both of the two fundamental including ($\pi_{t-1} - \pi_{t-1}^*$) and ($r_{t-1} - r_{t-1}^*$) as well as two time-series components including y_{t-1} and u_{t-1} as the explanation variables for the percentage change in the exchange rate, y_t . The potential disadvantage of the setting is to listen to each technique with equal concern. Specifically, we can rewrite the above equation as following:

$$y_t = \alpha + 1 \cdot [\beta_1^E (\pi_{t-1} - \pi_{t-1}^*) + \beta_2^E (r_{t-1} - r_{t-1}^*)] + 1 \cdot [\beta_1^T y_{t-1} + \beta_2^T u_{t-1}] \quad (4)$$

In detail, the above equation does is to introduce a method which consists of a specification including all the explanatory variables appearing in both of the separate forecasting equations. Moreover, the constant, 1 in the Equation 4 represents that the loading of the information from each technique is equal and fixed at any time point. Therefore, in the following discussions, we name the above specification as the composite model with constant weight.

(b) Composite Model with Non-constant Weight

For solving the potential demerit of the design of constant weight on each technique, we use the MS mechanism to design the following model specification:

$$y_t = \alpha + \beta_1^E (\pi_{t-1} - \pi_{t-1}^*) + \beta_2^E (r_{t-1} - r_{t-1}^*) + u_t^E, \quad u_t^E \sim N(0, \sigma^E), \text{ when } s_t=E$$

$$y_t = \alpha + \beta_1^T y_{t-1} + \beta_2^T u_{t-1} + u_t^T, \quad u_t^T \sim N(0, \sigma^T), \text{ when } s_t=T \quad (5)$$

,where s_t is an unobservable state variable and follows a Markov chain with one order:

$$\begin{aligned}
p(s_t = E | s_{t-1} = E) &= p_{EE}, & p(s_t = T | s_{t-1} = E) &= p_{ET} \\
p(s_t = T | s_{t-1} = T) &= p_{TT}, & p(s_t = E | s_{t-1} = T) &= p_{TE}
\end{aligned}
\tag{6}$$

In the above setting, we denote $s_t = E (T)$ to represent the state of econometric model (time-series approach). Here we want to denote that. Even the state variable, s_t is unobservable, but we can use the data to estimate the probability of specific regime at any time period. When the information set for estimation includes signals dated up to time t , the regime probability is $p(s_t/I_t)$ or filtering probability. On the other hand, one could also use the overall sample period T information set to estimate the state at time t : $p(s_t/I_T)$ or smoothing probability. In contrast, a predicting probability denotes the regime probability for an ex ante estimation, with the information set including signals dated up to the period $t-1$: $p(s_t/I_{t-1})$ ⁴.

Intuitively, at the standpoint of T , at the end of the test period, we can predict the smoothing probability measure is with more information. By the same logic, since we use the information from the current period in measuring the filtering probability, its accuracy and smoothness rank in between those of predicting and smoothing probabilities. In this paper, we use the smoothing probability (namely, $p(s_t/I_T)$, where I_T means the information set from the beginning period to the last period) to serve as the loading of each technique. Specifically, the prediction measure of the percentage

⁴ Please refer to Hamilton (1989) for the estimation process of the probability of specific state.

change in the exchange rate at the t period (namely, y_t^e) can be presented as the following:

$$y_t^e = \alpha + p(s_t = E | I_T) \cdot [\beta_1^E (\pi_{t-1} - \pi_{t-1}^*) + \beta_2^E (r_{t-1} - r_{t-1}^*)] + p(s_t = T | I_T) \cdot [\beta_1^T y_{t-1} + \beta_2^T u_{t-1}] \quad (7)$$

Comparing Equations 4 and 7, one can easily find the main difference between the two composite models. Specifically, the setting with constant weight uses an exogenous and equal loading to evaluate the impact of each forecasting technique. In contrast, the specification in Equation 7 employs an endogenous and non-constant loading. In other words, the probability of specific state (namely, $p(s_t/I_T)$) is estimated by data itself and will change over time. In the following discussions, we denote the model specification as the composite model with non-constant weight.

To conclude, even each composite model listens to the information from both of the fundamental variables and the own lagged values, nevertheless, the setting with constant weight ignore the characters that managers might more listen to the macroeconomic variables than lagged returns in some periods and vice versa. In other words, the loading on each forecasting technique might be changeable at different time point. Therefore, we establish a composite mode with non-constant weight in which adopts the MS mechanism to identify two possible regimes. Specifically, in the

regime of econometric model, the percentage change in the exchange rate depends on the fundamental variables in contrast with the regime of time-series approach in which the percentage change in the exchange rate listens to their own lagged values. Last, we employ the estimated probability of specific state at each time point to serve as the time-varying loading on each forecasting technique.

It is worth noting that we assume the constant term, α in Equations 5 and 7 is the same for the two different states. In contrast, Engle and Hamilton (1990) set up a setting with two measures of α to capture the long swing behaviors of the exchange rates. The behind ideas of our model designs are that we focus on distinguishing two sets of information, namely the fundamentals variables versus the own lagged values. Therefore, we define the constant term, α to be fixed at each state. In brief, all of the forecasting alternatives in this paper have one measure of constant term. This design is for excluding the potential noises from various settings on the constant term and concentrating on discussing the problems of how to weight the information from the two different sets of explanatory variables.

Furthermore, in the composite model with non-constant loading established by our paper, we set up two measures of the standard error to capture the behaviors that various techniques might correspond to various volatility measures. Specifically, in Equation 5, the technique of economic model (time-series approach) is associated

with the measure of volatility, σ^E (σ^T).

3. Empirical Results

The data used in this paper are the monthly bilateral exchange rates (in U.S. dollars per unit of foreign currency) for the currency of four industrialized countries (France, Germany, U.K. and Japan) and two Asian developing countries (South Korea and Taiwan). In the following discussions, the U.S. represents the foreign country and each of other six countries (including four industrialized and two Asian developing countries) represents the home country. The data period is from January, 1980 to August, 2000 for 248 observations. The proxies of interest rates and inflation rates are three-month treasury rates and change rates of CPI (consumer price index) index, respectively. Data source is AREMOS database.

We use OPTIMUM, a package program from GAUSS, and the built-in BFGS7 algebra to get the negative minimum likelihood (ML) function value of all specifications⁵. For examining the forecasting performances of various alternatives, we adopt two common criteria such as (1) MSE (Mean Square Error) and (2) MAE (Mean Absolute Error). The definitions of them can be expressed as:

$$MSE = T^{-1} \sum_{t=1}^T (y_t^e - y_t)^2 \quad (8)$$

⁵ We randomly generate 50 sets of initial values, and then derive the ML function value for each of the 100 sets of initial value respectively. The mapped converged measure of the greatest ML function value then serves to estimate the parameter.

$$MAE = T^{-1} \sum_{t=1}^T |y_t^e - y_t| \quad (9)$$

,where y_t^e and y_t denote the predicting and realized values of exchange rate returns, respectively and T is the number of observation. Moreover, we employ the random walk model as a benchmark to calculate the forecasting error reductions percentage relative to the random walk model for various alternatives.

Table 1 presents the percentage of forecast error reductions for various forecasting alternatives. Remarkably, the percentages of forecast error reduction of the composite model with non-constant weight are greater than zero and greater than the measures of other alternatives in most cases⁶. In contrast, the performances of the composite model with constant weight are unremarkable. In brief, the percentages of forecast error reduction of the composite model with constant weight are negative and less than one single forecasting technique for many cases. Our conclusion is clear. The design of time-varying loading established in this paper can enhance prediction performances on the exchange rates.

Panels (a) and (b) of Table 2 presents parameter estimates of the composite model with constant and non-constant weight, respectively. First, examining the

⁶ Except the MAE in the case of the U.K., the composite model with non-constant loading established in this paper performs a maximum forecasting error reduction performance for all cases.

results of the composite model with non-constant loading, the estimate of σ^E is greater than σ^T for all cases. Consequently, we denote the state of E (T) as the high (low) volatility state. These findings are consistent with the notion that the high (low) volatility market state will correspond to the forecasting technique of economic model (time-series approach).

Second, the two parameters of ARMA component (namely, β_1^T and β_2^T) in the composite with non-constant loading are significant for all cases⁷. In contrast, the two ARMA parameters in setting with constant weight are insignificant for the two cases of Japan and South Korea. These results are consistent with the notions that one can find more remarkable impacts of the own lagged data on the percentage change in the exchange rate after filtering out the high volatility periods.

Third, examining the significance of the two parameters of fundamental variables (namely, β_1^E and β_2^E) in the setting with non-constant loading, the β_1^E (β_2^E) is significant for the cases of France and Germany (U.K., Japan and Taiwan). However, both of the β_1^E and β_2^E are insignificant for the case of South Korea. These findings are consistent with the following notions that. During the high volatility periods, the fundamentals variables are invalid (valid) for the case of South Korea (other five cases).

⁷ In the case of the U.K., the β_2^T (β_1^T) is significant (insignificant). Moreover, both of β_1^T and β_2^T are significant for other five cases.

4. Economic and Financial Explanations for Our Empirical Results

In this section, we summarize our main empirical results and provide the economic and financial explanations to them. First, the composite model with non-constant loading on two forecasting techniques outperforms the setting with constant loading. This result is consistent with the notion that exchange markets would listen to both of fundamental variables and the own lagged values to determine the value of the exchange rate in the next period. Moreover, the loading of each set of explanatory variables is non-constant and will change over time.

Second, our empirical findings indicate that the high (low) volatility state corresponds to the forecasting technique of economic model (time-series approach). Here we provide an explanation for this result. From the perspective of nonlinear adjustment, one would strongly expect the speed of convergence toward theoretical values which are derived from economic theories should be greater as the deviation from theoretical values rise in absolute value. Moreover, because the theoretical exchange rates are stable, the great/small deviation from theoretical values should be well associated with the high/low volatility state. This is one of reasons of why the sate of economic model with the fundamental variables corresponds to the state of high volatility. On the other hand, the sate of time-series approach with the own lagged values corresponds to the sate of low volatility. This finding denotes that

investors might well picture the future exchange rates via their own past values during the stable periods.

Last, our empirical results indicate that, after filtering out the high volatility periods, the two lagged values in the ARMA approach are significant for all cases. However, during the volatile period, the fundamental variables are insignificant (significant) for the case of South Korea (other five cases). In Table 3, we use (σ^E/σ^T) to evaluate the measure of volatility at high volatility state relative to low volatility state for various currencies. Quite interesting, the values of (σ^E/σ^T) for industrialized countries' currencies are absolutely smaller than the developing ones. Specifically, 1.777, 1.590, 1.708 and 1.619 (13.543 and 4.158) are for France, Germany, U.K. and Japan (South Korea and Taiwan), respectively.

Regarding the above findings, our explanations are consistent with the following notions. In this paper, we use South Korea and Taiwan to serve as two representative developing countries. The policy of the two developing countries is to peg their currencies' value to the U.S. dollar, however, their currencies extremely suffered from the Asian crisis in 1997. By using France and South Korea as two representative examples, Figure 1 presents their monthly percentage changes in the exchange rate and smoothing probability of high volatility state (namely, the state of E). Apparently, the state-varying framework of MS model identifies the 1997 crisis period as a high

volatility regime for the case of South Korea. In contrast, the high volatility regime for the case of France is just an uncommon, not crisis, period. This is why the (σ^E/σ^T) values of developing countries' currencies are much greater than the industrialized ones.

Moreover, during the 1997 Asian crisis periods, South Korea was faced with substantial dollar depreciations and large scale of capital flights. These capital flights would more accelerate to diminish central bank's reserve, and cause central bank to lack strength to intervene the exchange market again. So the exchange rate volatility would be a larger amount than planned. This is why the value of (σ^E/σ^T) for the case of South Korea is much greater than other cases. Besides, the crisis period would be associated with investors' irrational overreaction behaviors. Furthermore, these irrational behaviors could provide a reason why the fundamental variables derived from the economic theories would be invalid during the extreme high volatility periods for the case of South Korea.

Unlike the case of South Korea, we denote the high volatility state of industrialized countries as an unusual condition, not a crisis situation. Therefore, we can find fundamental variables are valid on explaining the exchange rate during the volatile period. In detail, the inflation differentials (the interest rate differentials) are significant for the cases of the cases of France and Germany (U.K. and Japan).

Last, regarding the case of Taiwan, the state-varying framework of MS model also identify the 1997 Asian financial crisis period as a high volatility regime for it (not reported here). However, Taiwan was one of Asia's few star performers compared with its recession-hit neighbors during the Asian financial crisis in 1997⁸. Moreover, our empirical findings show that the value of (σ^E/σ^T) for the case of Taiwan is 4.513 and it is much smaller than the value of 13.543 for the case of South Korea. Therefore, we recognize the high volatility state of Taiwan as an unusual condition, not a crisis regime. Moreover, this can explain why the interest rate differentials are significant during the high volatility regime for the case of Taiwan.

5. Conclusion

In this paper, we adopt the MS mechanic to establish a composite model with an endogenous and non-constant loading on each of time-series approach and econometric model. The U.S. dollar exchange rates of the currencies of four industrialized countries including France, Germany, U.K. and Japan and two Asian developing countries including South Korea and Taiwan serve as the representative examples in this paper. Our empirical results are consistent with the following notions. First, the forecasting performances of the composite model with non-constant weight outperform other alternatives and random walk models in all cases. In contrast, the

⁸ One can also refer to "Taiwan Is Yet to Find Profit in Asia's Woes," A15, The Wall Street Journal, August 19, 1998.

performances of the composite model with constant weight are trivial. Second, the state of low (high) volatility regime corresponds to the state of the forecasting technique of time-series approach (econometric model). Third, after filtering out the high volatility periods, the AR and MA comments are remarkable. Last, we denote the high volatility state of the exchange market of South Korea as a crisis regime in contrast with an unusual condition for other cases. Moreover, the fundamental variables would be invalid during the crisis state for the case of South Korea; however, they are valid during the unusual condition for other cases.

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Table 1 Percentage of Forecast Error Reductions Relative to the Random Walk Model for Various Forecasting Alternatives

(a) Mean Square Error (MSE)

	Time Series Model	Econometric Model	Composite Model	
			Constant Weight	Non-constant Weight
Industrial countries				
France	2.623%	1.843%	-1.169%	5.356%*
Germany	0.896%	0.467%	1.830%	5.633%*
UK	3.208%	2.795%	2.008%	4.207%*
Japan	0.471%	3.044%	-2.013%	3.449%*
Developing Countries				
South Korea	0.718%	-0.567%	-0.957%	2.597%*
Taiwan	4.067%	-0.446%	-0.595%	7.866%*

(b) Mean Absolute Error (MAE)

	Time Series Model	Economic Model	Composite Model	
			Constant Weight	Non-constant Weight
Industrial countries				
France	1.982%	0.713%	-1.229%	5.141%*
Germany	0.357%	-0.159%	-0.318%	3.905%*
UK	0.206%	1.932%	2.795%*	2.020%
Japan	-1.444%	1.074%	-1.259%	2.896%*
Developing countries				
South Korea	0.639%	-2.958%	-5.116%	6.713%*
Taiwan	1.390%	-1.854%	-2.202%	4.114%*

Note:

1. The two loss functions are defined as the follows:

$$MSE = T^{-1} \sum_{t=1}^T (y_t^e - y_t)^2, \quad MAE = T^{-1} \sum_{t=1}^T |y_t^e - y_t|$$

, where y_t^e and y_t denote the predicting and realized values of exchange rate returns, respectively. T is the number of observation.

2. In this table, we adopt the random walk model as a benchmark to calculate the percentage of forecasting error reduction for each alternative.

3. * presents the maximum values in the row.

Table 2 Parameter Estimates of the Composite Models: Constant Weight versus Non-constant Weight

(a) Composite Model with Constant Weight

	α	β_1^T	β_2^T	β_1^E	β_2^E	σ	Log-Lik.
<i>Industrial Countries</i>							
<i>France</i>	0.145 (0.131)	0.630*** (0.198)	-1.868*** (0.648)	0.843* (0.492)	-0.532 (0.500)	3.187*** (0.143)	-636.798
<i>Germany</i>	0.085 (0.447)	-0.400* (0.243)	1.511* (0.799)	1.082* (0.593)	-2.038 (1.507)	3.252*** (0.146)	-641.727
<i>UK</i>	-1.263*** (0.445)	-0.561** (0.242)	1.653** (0.816)	0.445 (0.341)	5.227*** (1.554)	3.008*** (0.135)	-622.515
<i>Japan</i>	-0.866** (0.377)	0.111 (0.255)	-0.301 (0.864)	-0.319 (0.355)	-2.354** (1.182)	3.482*** (0.157)	-658.666
<i>Developing Countries</i>							
<i>South Korea</i>	0.187 (0.232)	0.421 (0.342)	-0.993 (0.834)	-0.351 (0.312)	0.098 (0.628)	3.338*** (0.15)	-648.24
<i>Taiwan</i>	-0.038 (0.177)	0.885*** (0.086)	-0.776*** (0.117)	0.039 (0.09)	1.033 (0.826)	1.403*** (0.190)	-429.745

(b) Composite Model with Non-constant weight

	α	β_1^T	β_2^T	β_1^E	β_2^E	σ^T	σ^E	P_{TT}	P_{EE}	Log-Lik.
<i>Industrial Countries</i>										
<i>France</i>	-0.013 (0.029)	0.994*** (0.043)	-0.894*** (0.088)	0.604* (0.363)	0.481 (1.779)	2.307*** (0.357)	4.100*** (0.555)	0.571** (0.293)	0.359* (0.221)	-633.096
<i>Germany</i>	0.133 (0.292)	-0.606*** (0.089)	0.900*** (0.033)	1.056* (0.613)	-1.165 (1.581)	2.424*** (0.198)	3.854*** (0.290)	0.973*** (0.020)	0.971*** (0.023)	-634.158
<i>UK</i>	-0.160 (0.168)	0.079 (0.246)	-0.370* (0.230)	0.171 (0.520)	1.895*** (0.897)	2.026*** (0.172)	3.460*** (0.197)	0.994*** (0.197)	0.996*** (0.006)	-615.810
<i>Japan</i>	-0.975*** (0.389)	-0.673*** (0.192)	0.844*** (0.124)	-0.232 (0.424)	-2.706** (1.364)	2.335*** (0.308)	3.813 (0.238)	0.951 (0.036)	0.984 (0.014)	-656.062
<i>Developing Countries</i>										
<i>South Korea</i>	0.017 (0.025)	0.877*** (0.100)	-0.564*** (0.250)	-1.193 (2.026)	1.469 (2.938)	0.635*** (0.068)	8.600 (1.270)	0.981 (0.013)	0.884 (0.070)	-355.370
<i>Taiwan</i>	-0.013 (0.017)	0.793*** (0.096)	-0.701*** (0.110)	0.256 (0.470)	4.640* (2.698)	0.652*** (0.063)	2.711*** (0.365)	0.881*** (0.045)	0.553*** (0.140)	-367.134

Note:

1. The ***, ** and * denote the significance in 1%, 2.5% and 5 %, respectively.
2. The value in the parenthesis denotes the stand error of the parameter estimate.

Table 3 Measure of Volatility at High Volatility State Relative to Low Volatility State

Parameter	Industrialized Countries				Developing Countries	
	France	Germany	UK	Japan	South Korea	Taiwan
(σ^E/σ^T)	1.777	1.590	1.708	1.619	13.543	4.158

Note: We use (σ^E/σ^T) to evaluate the measure of volatility at high volatility state relative to low volatility state for various currencies. Quite interesting, the values of (σ^E/σ^T) for industrialized countries' currencies are absolutely smaller than the developing ones

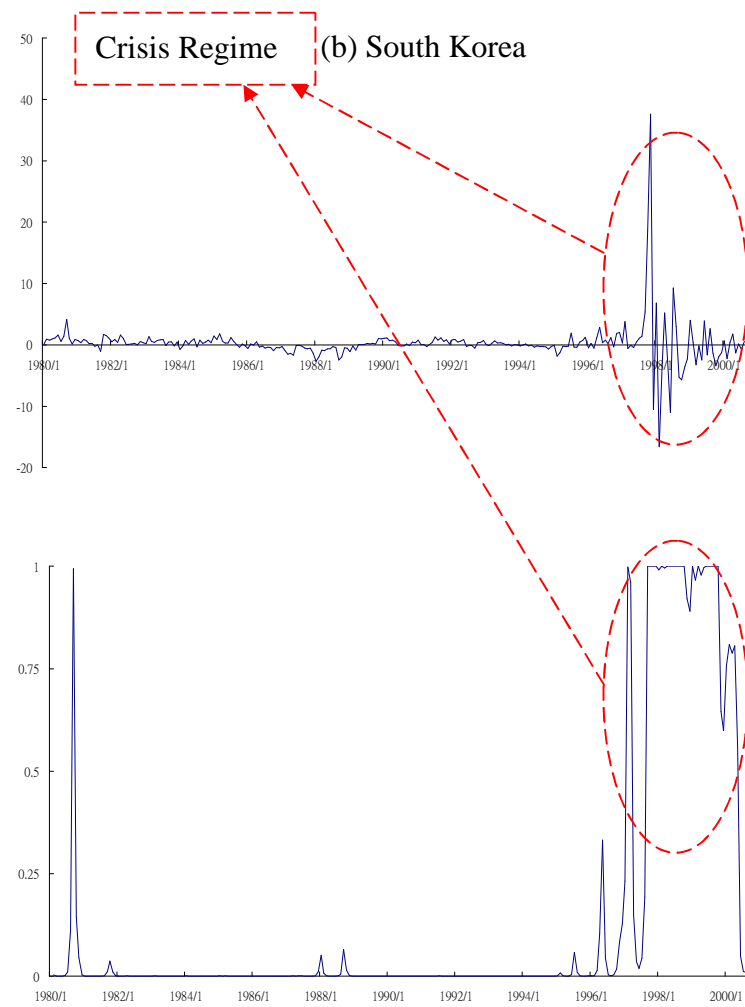
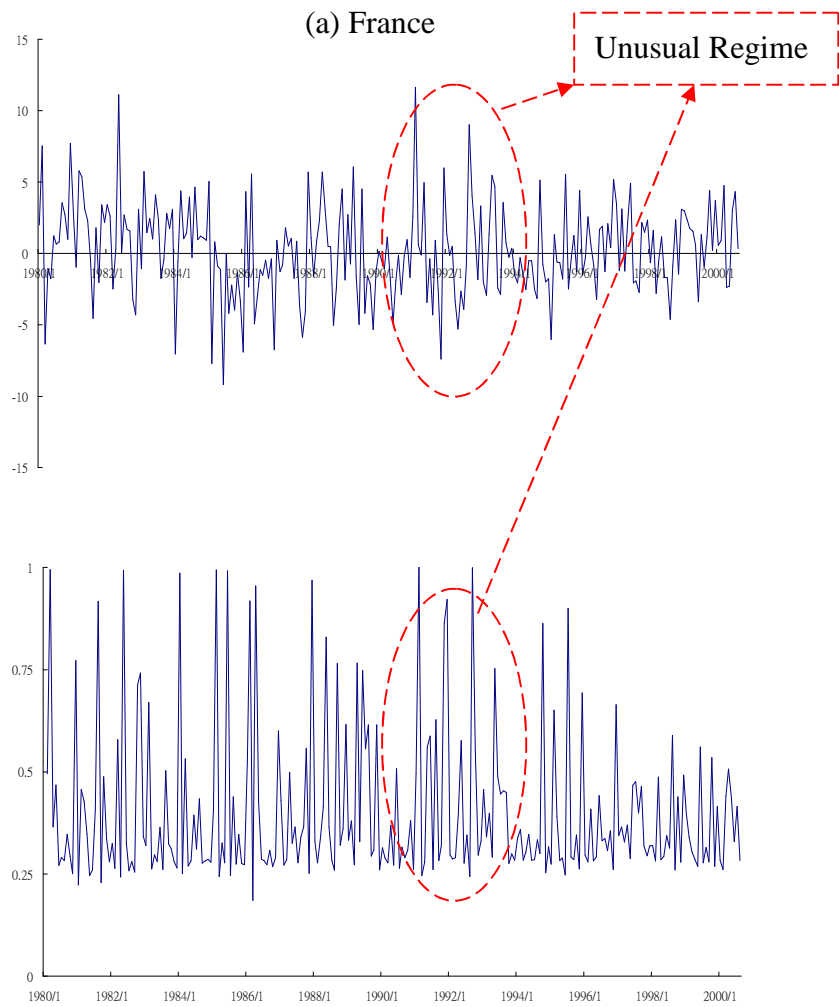


Figure 1 Monthly Percentage Change in the Exchange Rate and Smoothing Probability of High Volatility State for Exchange Markets of France and South Korea