Regime-Switching Analysis for the Impacts of the Exchange Rate Uncertainty on the Taiwan’s Corporate Values

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Abstract

A second-moment regime-switching regression, which considers not only a switching intercept and a switching slope, but a switching error variance is applied to investigate the impacts of the exchange rate uncertainty (ERU) on the corporate values (CVs) for the industries concerned in Taiwan. Two different regimes of a strong-impact and a weak-impact are identified. However, the dominant power varies from industry to industry. The Wald statistics for the null of equality are mixed, which shows that if the Markov-switching (MS) model is appropriate, the ERU might not be the major factor but other factors, which could switch the CVs of Taiwan’s industries. Nonetheless, for the model’s volatility influence, the data of eight industries are shown to fit a two-state model when the volatility is stimulated. Finally, based on the 10% significant level, a two-state first-order MS model is appropriate for the "goodness of fit" analysis.

Key words: Exchange rate uncertainty, Corporate values, GARCH, Markov switching model

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I. Introduction

The controversial issue of the impact of the exchange rate uncertainty (ERU hereafter) on the exporting volume is mixed. Literature has mostly described that the increased uncertainty caused by a higher exchange rate fluctuation would hurt the exports when firms are risk-averse. However, the other theory-based results as in Broll and Eckwert (1999) indicate that "the higher volatility increases the potential gains from trade, which in turn stimulates the exports." A positive relationship between the exchange rate volatility and the exports is thus asserted. As an export-led country, Taiwan's corporate values (CVs hereafter) have long been highly affected by its exporting volumes. After the government of Taiwan adopted the managed floating exchange rate system since 1979, the international trading volumes have dramatically increased owing to the more liberalization of the enterprises' foreign trade activities. The deregulation in the foreign exchange market of Taiwan seems to have provided many trading corporations and many multinational corporations (MNCs) more opportunities to expand their business activities. However, the drastic changes in the NT dollar (NTD) against the US dollar (USD) have caused these enterprises to lose the firm values.¹ (see Figure 1 for the exchange rate movement of NTD/USD for the last three decades) This can be verified in many home enterprises that went into bankruptcy when they encountered the significant uncertainty in the exchange rate levels. As a result, the ERU does pave Taiwan's corporations another way in achieving the market-expansion and profit-pursuing goals, the increased volatility raises business and financial risks to the deeply trading corporations.

<Insert Figure 1 about here>

As mentioned above, the exporting volume is usually used as a proxy for the CV since, for an export-led country, the CVs are highly influenced by the country's exporting volumes. Several literatures within the last two decades have investigated the issue of the relationship between the ERU and the exporting flows, and most empirical evidence found the result of the significantly negative relationship. The examples are in the papers of Arize (1995), Chowdhury (1993), Hassan (1998), Smith (1999), Arize, Osang and Slottje (2000), and Nieh (2002). Other studies also focused on the relationship between the ERU and the trading volumes. For instance, Gupta

¹ Generally acknowledged, there had been three drastic changes in the NTD against the USD since the regime of managed floating exchange rates was adopted by the government of Taiwan in February of 1979. The first one was that after the "Plaza Accord", the NTD followed the Japanese yen to appreciate within six months from June to November, 1986. The second one was the drastic depreciation a few months after the Asian financial crisis happened in July 1997.
(1980) finds that two out of five countries considered show the significantly negative relationship between the ERU and the trading volume. The similar results are obtained from Rana (1981) for South Korea, Taiwan and Philippine, from Coes (1981) for Brazil, from Cushman (1983) for six out of fourteen developed countries, and from Akhtar and Hilton (1984) for the United States and Germany. The more literatures reaching the same results can also be seen in Kenen and Rodrik (1986), Chowdhury (1993), Arize (1997), Broll, Wong and Zilcha (1999), and Arize, Osang & Slottje (2000). However, among the studies of Gotur (1985), De Grauwe (1988), Perree and Steinherr (1989), Franke (1991), Viaene and Vries (1992), and Broll and Eckwert (1999), etc., they show an opposite result that the positive relationship exists between the exchange rate volatility and the volume of trade.

In general, the perspectives mentioned above ignore the fact that the switching property exists in the influence of ERU on the trading volumes or the corporate values and thus a time-invarying measure is not appropriate. In other words, the impact on CVs has to account for regime-switching to infer the persistence of a stronger or a weaker influence power of the ERU.

The two-state first-order Markov-switching (MS) model was first cited in Hamilton (1988) and have thereafter been widely employed to analyze economic and financial time series. For example, Shen (1994) tests the hypothesis the efficiency of the Taiwan-US forward exchange market, and Ho (2000a) tests the hypothesis for the international capital mobility. Moreover, Huang (2000) and Ho (2000b) employ the same technique to examine the Sharpe-Lintner CAPM and the Phillips curve trade-off, respectively. The applications of the MS mechanism can also be found in Engel and Hamilton (1990), Garcia and Perron (1993), Engle (1994), Kim and Yoo (1995), and Schaller and van Norden (1997). The hypothesis for the MS model was that samples were drawn from a finite mixture of distributions. The transition probabilities in the Markov-chain pattern offer the information that the description ability is time-varying. It also provides insight into the situation in which one regime dominates another. In our example, say that, if the impact level is currently in regime I (strong-impact state or weak-impact state), then there is a probability of $p_{ii}$ for the next impact level to stay in the same regime.

Based on the controversies between more opportunities to achieve the corporate goals and the harmful experiences of the large movements of exchange rates, this paper attempts to investigate the impacts of the Taiwan’s corporate values among industries due to the uncertainty of exchange rates. Following Arize (1995, 1997) we

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2 The elaborated work of the Hamilton’s MS model adopts the spirit of the probability switching mechanism by Goldfelt and Quandt’s (1973) for the heteroscedasticity, which categories two unobserved regimes (states), each with a fixed probability, by the observed data.
first apply the GARCH modeling to extract the values of volatility as a measure of the ERU. Second, the use of the OLS approach tests for the effects of the uncertainty in the corporate values among different industries. Finally, the impact of the ERU on the CVs is investigated by employing a two-state first-order MS model. As suggested by Ho (2000a, 2000b) and Huang (2000), this paper extends their simple first-moment switching model to a second-moment model to allow for variance to be drawn from different states, i.e., there exist a higher volatility and a lower volatility regime when the corporate values are influenced by the ERU. In other words, we consider a MS model not only with a switching intercept and a switching slope, but with a switching error variance.

This paper is organized as the following way. The data sources are reported in Section II. Section III describes the way to extract the ERU and shows the results. Section IV presents the techniques of the traditional OLS and CUSUM tests. The methodologies coping with the switching technique are described in Section V. In Section V, the empirical results are also reported and analyzed. A concluding remark concerning this paper in Section VI. A derivation of the theoretical model which shows the relationship between the ERU and the CVs is presented in the appendix.

II. Data

Monthly data are used in this paper for the period running from January 1988 to February 2000. The exchange rates of NT dollar against US dollar are collected from AREMOS of the Ministry of Education, Taiwan, whereas the CVs are from TEJ (Taiwan Economic Journal) published monthly in Taiwan. The samples of the corporate values are those from the export-led listing companies in the Taiwan’s stock market. For the explaining power, this paper only selects ten major industries from the listing companies, which include food, rubber, textile, electricity, chemistry, glass, steel, plastic, paper, and electron. We calculate the weighted average of the corporate values by using the close stock prices and the outstanding shares from each industry. Moreover, for comparison, we categorize three categories based on the percentage of the exporting volume for the export-led listing companies, which are the industries with the export ratios under 30 percent, between 30 and 50 percent, and over 50 percent, respectively. Totally, we have fourteen entities (including exchange rates of NTD/USD) and 146 observations for each entity. Besides, for each series, the data are

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3 The original MS model focuses on the mean behavior of variables. We take into account the probability of conditional heteroscedasticity of the disturbance term to examine the time-varying two-state unobserved variances, which emerged from the impulse of CVs to ERU.

4 The applications of the extended MS model accommodating the pattern of conditional volatility can be found in Hamilton and Lin (1996), Dueker (1997), and Ramchand and Susmel (1998).
adjusted by the ratios to moving average (multiplication) to remove the monthly
cyclical seasonal fluctuation

For simplicity, each series are represented by symbols as follows: Y1 for chemistry, Y2 for electron, Y3 for food, Y4 for glass, Y5 for electricity, Y6 for paper, Y7 for plastic, Y8 for rubber, Y9 for steel, Y10 for textile, Y11 for the export ratio over 50%, Y12 for the export ratio under 30%, Y13 for the export ratio between 30% and 50%, and RX for the exchange rate volatility (uncertainty).

III. GARCH modeling for ERU

Following the application in Arize (1995) and Arize (1997), a generalized
autoregressive conditional heteroscedasticity (GARCH) model is employed for
measuring the exchange rate volatility. A GARCH(1,1) modeling is as follows:

\[ e_t = \pi_0 + \pi_1 e_{t-1} + \mu_t \]  
\[ h_t = \alpha_0 + \alpha_1 \mu_{t-1}^2 + \beta_1 h_{t-1} \]

To generate the ERU, we assume that the exchange rates follow an AR(1) process. In
Equation (1), \( \mu_t \) is a realized disturbance term, \( e_t \) denotes the exchange rates, \( \alpha_1 \), \( \beta_1 \)
and \( \pi_1 \) are the coefficients, and \( h_t \), the heteroscedastic variance, represents the ERU
in this paper.

We first apply the LM-test for investigating the property of heteroscedasticity. As
we observe from Table 2 that, when examining the residuals of the model by the
LM-test, the null hypothesis of no GARCH effect is rejected at the 5% significance
level. Therefore, the use of the GARCH(1, 1) modeling to extract the values of
exchange rate volatility is appropriate. In addition, from the estimation of the
coefficients of \( \alpha_1 \) and \( \beta_1 \), we find that both of them are away from zero at the 5%
significance level. Moreover, the estimates of \( \alpha_1 \) and \( \beta_1 \) are summed up to close to one,
which supports evidence of a clutch phenomenon of the persistent volatility (see
Figure 2).\(^5\)

\[ \text{<Insert Table 1 about here>} \]
\[ \text{<Insert Figure 2 about here>} \]

\(^5\) The result of an existing GARCH effect for the ERU of NTD/USD is consistent with those findings
in Pozo (1992), Arize (1995) and Arize (1997), which measured the ERU of the US and the G-7
countries
IV. The OLS and the CUSUM

In order to investigate the influence of the exchange rate uncertainty on each of the corporate values, the ordinary least squares (OLS) method is commonly used:

\[ R_t = \alpha + \beta V_t + \epsilon_t \]  

(2)

where \( R_t \) denotes the corporate values, \( V_t \) is the exchange rate volatility, and \( \epsilon_t \sim iid \ N(0,\sigma^2) \) is a white noise.

The OLS estimation presents in Table 2 shows that the ERU possesses a positive effect on the values of chemistry, electron, plastic, rubber industries, and all three categories of the export ratios while it has a negative impact on that of food industry. However, for the rest of the industries considered, the exchange rate volatility does not show any significant explaining power.

<Insert Table 2 about here>

To assert the findings of the OLS regression analysis, the "stability" of the data set seems critical. To examine this, the goodness-of-fit type tests of cumulative sum of residuals (CUSUM) and CUSUM of squares based on recursive residuals are employed for the unknown structural break (see Brown, Durbin, and Evans (1975)). The equations for CUSUM and CUSUM of squares models are represented as follows, respectively:

\[ W_m = \frac{1}{\sigma} \sum_{t=k+1}^{m} w_t \quad m = k + 1, ..., T \]  

(3)

\[ S_m = \frac{\sum_{t=k+1}^{m} w_t^2}{s^2} \quad , \quad s^2 = \sum_{t=k+1}^{T} w_t^2 \quad m = k + 1, ..., T \]  

(4)

where \( w_t \) denotes the recursive residual and \( \sigma \) is the estimated standard deviation. If the path of \( W_m \) (Equation (3)) or \( S_m \) (Equation (4)) crosses the boundary for some \( m \), say, 5% significance level, we reject the null hypothesis of no structural break, which is the case of being unstable.

Though we can analyze the impacts of the ERU on the CVs of industries investigated from Table 2, the relatively lower \( R^2 \) seems as if the OLS results are not reliable. This can be answered through the results of the CUSUM and CUSUM of squares tests, which are presented in Figure 3. These figures show that, from all the plots, the paths of recursive residuals cross the boundary. The null of "stability" is thus rejected significantly at the 5% critical level. This evidential existence of structural breaks in the model provides the possibility of the relatively lower \( R^2 \).
V. Markov Switching

Even though we can analyze the parameters of the OLS formula to describe the impacts of the ERU on the CVs, the realized lower $R^2$ infers that the predicted power of the OLS model seems inadequate. The two observed structural changes within the sample period of the exchange rate volatility (see Figure 1) and the "non-stationary" property for most of the series might be the reason for reducing the values of $R^2$.\textsuperscript{6} This can also be explained by the rejection of the null of "stability" from the CUSUM and CUSUM of squares plots, as described above (see Figure 2). Moreover, the constant estimated parameters from the OLS are not appropriate in describing the time-varying relationships between variables considered. To remedy for these problems, we employ the basic idea of the Hamilton’s (1988, 1989) settings of the two-state first-order MS model by maximum likelihood and further extend to consider the time-varying error variance as suggested in Ho (2000a, 2000b) and Huang (2000). The OLS model, $R_t = \alpha + \beta X_t + \varepsilon_t$, is thus transferred to the following MS setting with MS mean and variance.

$$R_{it} = \alpha_{it} + \beta_{it} V_t + \varepsilon_{it}, \quad \varepsilon_{it} \sim N(0, \sigma^2_{it})$$ \hspace{1cm} (5)

where $R_{it}$ denotes the CVs for industry $i$ at time $t$. $V_t$ is the ERU at time $t$. $s_t$ is the unobserved state variable presumed to follow a two-state Markov chain with transition probability ($p_{ij}$). $\beta_{it}$ is the influence parameter in state $s_t$, which measures the impacts of the ERU on the CVs for industry $i$. $\sigma_{it}$ is the standard deviations in state $s_t$, which measures the risks from the CVs of industry $i$.

Equation (5) is assumed to follow a regime-switching framework by quasi-maximum likelihood as described in Hamilton (1989). The testable scheme is expressed as follows.

$$\alpha_{s_t} = \begin{cases} \alpha_{i1} & \text{if } s_t = 1 \\ \alpha_{i2} & \text{if } s_t = 2 \end{cases}, \quad \beta_{s_t} = \begin{cases} \beta_{i1} & \text{if } s_t = 1 \\ \beta_{i2} & \text{if } s_t = 2 \end{cases}, \quad \sigma_{s_t} = \begin{cases} \sigma_{i1} & \text{if } s_t = 1 \\ \sigma_{i2} & \text{if } s_t = 2 \end{cases}$$

where the two states represent two regimes. The coefficients are $(\alpha_{i1, \beta_{i1, \sigma_{i1}}})$ in regime 1 and $(\alpha_{i2, \beta_{i2, \sigma_{i2}}})$ in regime 2, respectively. The evolution of the unobservable state variable is assumed to follow a two-state first-order Markov chain satisfying $p_{11} + p_{12} = p_{21} + p_{22} = 1$, where $p_{ij} = \Pr(s_t = j | s_{t-1} = i)$ gives the

\textsuperscript{6} The non-stationary property is obtained from the ADF (Dickey and Fuller, 1981) unit-root test, which is omitted in this paper, however, those will be available upon request.
probability that state i followed by state j. The state in each time point determines which of the two normal densities is used to generate the model. For our case of the ERU-CV relationship, it is assumed to switch between two regimes (say, strong-impact state and weak-impact state) according to transition probabilities. When the current ERU-CV relationship is in regime 1, there is \( p_{11} \) chance for the next ERU-CV relationship to stay in the same regime; the same argument can be applied to regime 2 for holding \( p_{22} \) chance to stay in the same regime.

**Quasi-Maximum Likelihood Estimation of parameters**

There are various ways to estimate the MS model (see Kim and Nelson, 1999). The estimation of the MS setting of equation (5) mainly follows Garcia and Perron (1996), which employs Hamilton’s (1989) MS estimation by quasi-maximum likelihood.\(^8\)

Let \( y_t = R_t, \ x_t = (I, V_t)' \) and \( \delta_t = (\alpha_t', \beta_t') \). Equation (5) can be expressed as: \(^9\)

\[
y_t = x_t \delta_t + \varepsilon_t, \quad \varepsilon_t \sim N(0, \sigma_t^2)
\]

This MS model assumes that the variance is also shifting between regimes. \( s_t \) is the unobserved state variable presumed to follow a two-state Markov chain with transition probability \( (p_{ij}) \).

As usual, we use capital letters \( X_t \) and \( Y_t \) to represent all the information available up to time \( t \) and \( \theta \) to denote the vector of the unknown population parameters.

\[
i.e., \ X_t = (x_t, x_2, \ldots, x_T)' \quad Y_t = (y_1, y_2, \ldots, y_T)' \quad \text{and} \quad \theta = (\theta_1, \theta_2)',\]

\( X_t \) is exogenous or predetermined and conditional on \( s_{t-1} \), and \( s_t \) is independent of \( X_t \). The grouping parameter vector can be decomposed by \( \theta_1 = (\alpha, \alpha_2, \beta, \beta_2, \sigma, \sigma_2) \) and \( \theta_2 = (p_{11}, p_{22}) \).

By denoting \( \tilde{X}_T = (x_1, x_2, \ldots, x_T)' \), \( \tilde{Y}_T = (y_1, y_2, \ldots, y_T)' \), and

\[
\tilde{S}_T = (s_1, s_2, \ldots, s_T)',
\]

the joint density of \( \tilde{Y}_T \) and \( \tilde{S}_T \) is as:

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\(^7\) Markov property argues that the process of \( s_t \) depends on the past realizations only through \( s_{t-1} \).

\(^8\) Garcia and Perron (1996) employs Hamilton’s (1989) MS model to explicitly account for regime shifts in an autoregressive model with three-state MS mean and variance.

\(^9\) For simplicity, the following analysis is based only on one industry. We thus omit the symbol \( i \).
\[ f(\tilde{Y}_t, \tilde{S}_t; \tilde{X}_t, \theta) = f(\tilde{Y}_t / \tilde{S}_t; \tilde{X}_t, \theta_1) \times f(\tilde{S}_t; \tilde{X}_t, \theta_2) \]
\[ = \prod_{t=1}^{T} f(y_t / s_t; x_t, \theta_1) \times \prod_{t=1}^{T} f(s_t / s_{t-1}; x_t, \theta_2) \]

The log likelihood function can thus be expressed as:

\[ \ln(\tilde{Y}_t, \tilde{S}_t; \tilde{X}_t, \theta) = \sum_{t=1}^{T} \ln[f(y_t / s_t; x_t, \theta_1)] \times \sum_{t=1}^{T} \ln[f(s_t / s_{t-1}; x_t, \theta_2)] \]

If the state is known, the parameter vector \( \theta_2 \) would be irrelevant and the log likelihood function would be maximized with respect to \( \theta_1 \).

\[
\frac{\partial \ln[f(\tilde{Y}_t, \tilde{S}_t; \tilde{X}_t, \theta)]}{\partial \theta_1} = \sum_{t=1}^{T} \frac{\partial \ln[f(y_t / s_t; x_t, \theta_1)]}{\partial \theta_1}
\]

Now, let’s introduce the estimation proceeds as the following way.

**Filter probability**

We assume that \( \theta \) is already observed. Based on Hamilton (1994), the derivation begins with the unconditional probability of the state of the first observation.

\[ p(s_t = 1) = \frac{1 - p_{22}}{(1 - p_{11}) + (1 - p_{22})} = \gamma, \text{ and consequently } p(s_t = 2) = 1 - \gamma \]

Given \( Y_{t-1} \), the joint probability of \( s_{t-1} \) and \( s_t \) is:

\[ p(s_t, s_{t-1} / Y_{t-1}; X_t) = p(s_t / s_{t-1}, Y_{t-1}; X_t) \times p(s_{t-1} / Y_{t-1}; X_{t-1}) \]

\[ = p(s_t / s_{t-1}) p(s_{t-1} / Y_{t-1}; X_{t-1}) \quad (6) \]

where the first equality is given by Bayes’ theorem and the second one is by the independence principle of the Markov chain. Since the transition probability \( p(s_t / s_{t-1}) \) and the filter probability at time \( t-1, p(s_{t-1} / Y_{t-1}; X_{t-1}) \), are both known at time \( t \), it is not difficult to calculate \( p(s_t, s_{t-1} / Y_{t-1}; X_t) \) in Equation (6).

Summing up \( s_{t-1} \) to get the conditional marginal distribution of \( s_t \):

\[ p(s_t / Y_{t-1}; X_t) = \sum_{s_{t-1}=1}^{2} p(s_t, s_{t-1} / Y_{t-1}; X_t) \quad (7) \]

The joint probability of \( y_t \) and \( s_t \) at time \( t \) is then calculated as:

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10 The following derivations are mainly from Shen (1994).

11 \( f(.) \) and \( p(.) \) denote the continuous and discrete density function, respectively.
\[ p(y_t,s_t/Y_{-t};X_t) = f(y_t/s_t,Y_{-t};X_{-t}) \times p(s_t/Y_{-t};X_{-t}) \] (8)

The first term on the right hand side is the sample likelihood function and the second term is from Equation (7), so Equation (8) can be calculated. Therefore, the filter inference about the probable regime at time \( t \) is given by:

\[
P(s_t/Y_t;X_t) = \frac{p(y_t,s_t/Y_{-t};X_t)}{p(y_t/Y_{-t};X_t)} = \frac{f(y_t/s_t,Y_{-t};X_t) \times p(s_t/Y_{-t};X_t)}{\sum_{s_{t+1}=1}^2 f(y_t/s_t,Y_{-t};X_t) \times p(s_t/Y_{-t};X_t)}
\]

**Smoothed probability**

The derivation of filter probability utilizes the information up to time \( t \). Alternatively, we can use the full sample of ex post available information to draw the inference. It is therefore more efficient in the sense that all the information up to time \( T \) is utilized instead of \( t \). Similarly, the smoothed probability of the first observation has to be derived. Consider the joint probability of \( y_t, s_t \) and \( s_t \):

\[
p(y_t,s_t,Y_{-t};X_t) = f(y_t/s_t,s_t,Y_{-t};X_t) \times p(s_t,Y_{-t};X_{-t})
= f(y_t/s_t,s_t,Y_{-t};X_t) \times p(s_t,Y_{-t};X_{-t})
\]

where the first equality is given by Bayes’ theorem and the second one is by the Bayes’ theorem and independence principle of Markov chain. The first term on the right hand side of Equation (9) is the sample likelihood function. The second term can be derived by:

\[
p(s_t/s_1) = \sum_{s_{t-1}=1}^2 p(s_t,s_{t-1}/s_1)
= \sum_{s_{t-1}=1}^2 p(s_t/s_{t-1}) p(s_{t-1}/s_1)
= \sum_{s_{t-1}=1}^2 \sum_{s_{t-2}=1}^2 p(s_t/s_{t-1}) p(s_{t-1}/s_{t-2}) p(s_{t-2}/s_1)
\]

and the third term is the filter probability at time \( t-1 \). These terms are all known at
time \( t \) and can be used to calculate Equation (9).

The joint probability of \( s_i \) and \( s_{i+1} \) is thus given by:

\[
P(s_i, s_j|Y; X) = \frac{p(y_j, s_j, s_{j-1} / Y_{j-1}; X_j)}{p(y_j / Y_{j-1}; X_j)}
\]

The numerator is from Equation (9) and the denominator can be derived by summing up \( s_i \) and \( s_{i+1} \) of Equation (9). The conditional marginal probability of \( s_i \) is then given by summing up \( s_i \):

\[
p(s_j / Y_j; X_j) = \sum_{s_i=1}^{2} p(s_i, s_j / Y_j; X_j)
\]

and this is the smoothed probability of the first observation at time \( t \). Similarly, the smoothed probability at time \( t+1 \) can be obtained by:

\[
P(s_{i+1}, s_j / Y_{i+1}; X_{i+1}) = \frac{p(y_{i+1}, s_{i+1}, s_{i+1} / Y_{i+1}; X_{i+1})}{p(y_{i+1} / Y_{i+1}; X_{i+1})}
\]

where,

\[
p(y_{i+1}, s_{i+1}, s_{i+1} / Y_{i+1}; X_{i+1}) = f(y_{i+1} / s_{i+1}, s_{i+1}, Y_i; X_{i+1})
\]

\[
\times p(s_{i+1}, s_{i+1} / Y_i; X_{i+1}) = f(y_{i+1} / s_{i+1}, s_{i+1}, Y_i; X_{i+1})
\]

\[
\times p(s_{i+1} / s_{i+1}) p(s_{i+1} / Y_i; X_{i+1})
\]

and

\[
p(s_{i+1} / s_{i+1}) = \sum_{s_{i+1}=1}^{2} \sum_{s_i=1}^{2} \sum_{s_{i-1}=1}^{2} p(s_i / s_{i-1})
\]

\[
\times p(s_{i+1} / s_i) p(s_{i+1} / s_{i-1}) ... p(s_2 / s_1)
\]

Summing up \( s_{i+1} \) to get the smoothed probability of the first observation at time \( t+1 \) yields:

\[
p(s_i / Y_{i+1}; X_{i+1}) = \sum_{s_{i+1}=1}^{2} p(s_{i+1}, s_i / Y_{i+1}; X_{i+1})
\]

By repeating the above steps, we are able to get the smoothed probability of the first observation at time \( T \):

\[
p(s_i / Y_T; X_T) = \sum_{s_{T}=1}^{2} p(s_T, s_i / Y_T; X_T)
\]

Similarly, the smoothed probability of the \( i \)th observation at time \( T \) is given by:

\[
p(s_i / Y_T; X_T) = \sum_{s_{T}=1}^{2} p(s_T, s_i / Y_T; X_T), \quad t = 1, 2, ..., T
\]
Estimation

According to the smoothed probability derived in the previous section, we can say that the observations were generated from the first state with probability \( p(s_t = 1 \mid Y_T; X_T) \) and from the second state with probability \( p(s_t = 2 \mid Y_T; X_T) \). Hamilton(1994) shows the relevant conditions of the maximum likelihood estimates of the \( \phi_h \) are:

\[
\sum_{t=1}^{T} (y_t = x_t' \hat{\phi}_j) x_t \times p(s_t \mid Y_t; X_t) = 0, \quad j = 1, 2 \tag{10}
\]

\[
\sigma^2 = \frac{\sum_{t=1}^{T} \sum_{j=1}^{2} (y_t - x_t' \hat{\phi}_j) \times p(s_t \mid Y_t; X_t)}{T} \tag{11}
\]

Equation (10) implies that \( \hat{\phi}_j \) satisfies a weighted OLS orthogonality condition where each observation is weighted by the probability that it came from regime j. In particular, \( \hat{\phi}_j \) can be found from an OLS regression of \( y_t^*(j) \) on \( x_t^*(j) \):

\[
\hat{\phi}_j = \left[ \sum_{t=1}^{T} x_t^*(j) x_t^*(j)' \right]^{-1} \left[ \sum_{t=1}^{T} x_t^*(j) y_t^*(j)' \right], \quad j = 1, 2
\]

where,

\[
y_t^*(j) = y_t \times \sqrt{p(s_t = j \mid Y_T; X_T)}
\]

\[
x_t^*(j) = x_t \times \sqrt{p(s_t = j \mid X_T; Y_T)}
\]

where \( j \) denotes the present state and “ \( * \) “ is used to distinguish the terms of the weighted observations from the original observations. The estimate of \( \sigma^2 \) in Equation (11) is just the combined sum of the squared residuals from these two regressions divided by T.

Hamilton(1994) also shows the maximum likelihood estimates for the transition probabilities:

\[
p_{ij} = \frac{\sum_{t=2}^{T} p(s_t = j, s_{t-1} = i \mid Y_T; X_T)}{\sum_{t=2}^{T} p(s_{t-1} = i \mid Y_T; X_T)}
\]

which is essentially the number of times state \( i \) followed by state \( j \) divided by the number of times the process was in state \( i \).
The results of the maximum likelihood estimation (Equation, 10 and 11) for the time-varying relationships between the variables concerned are reported in Table 3. The constant terms of $\alpha_1$ and $\alpha_2$ for both regimes are all shown to be significantly away from zero at the 1% critical value for all industries. However, the findings of the impact coefficients $\beta_1$ and $\beta_2$ of regime 1 and regime 2 are mixed. The results show that the strong or weak-impact power exists in different regimes from industry to industry. As we can observe from Table 3, the impact coefficients $\beta_2$’s of regime 2 for industrial categories of Y1, Y2, Y7, Y8, and Y11 while the impact coefficients $\beta_1$’s of regime 1 for industrial categories of Y3, Y4, Y5, Y9, Y12, and Y13 are all significantly different from zero, which implies a strong-impact on the CVs caused by the ERU. Those $\beta$’s which are not shown to be significant imply a weak-impact phenomenon. This paper also investigates the switching possibility existing in the variance (say, a high volatility and a low volatility regimes) of the model when the CVs are influenced by the ERU. The same results as those of constant terms are found that, no matter which of regime 1 or regime 2, all the volatility factors $\sigma_1$ or $\sigma_2$ are shown to be significant at the 1% critical level for all industries. These strong influence phenomena existing among all the industries illustrate that the ERU is not the only factor affecting the values of industries, but the variance stirs up from the model. Investors having keen insights into the investment decisions should focus on the risks arising from the industries themselves.

Moreover, the associated transition probability can be used to analyze which regime has a stronger dominant power. The results in Table 3 show that the transition probabilities of the regime 1 dominate that of regime 2 for industrial categories of Y1, Y4, Y5, Y6, Y7, Y8, Y9, Y12, and Y13. On the other hand, for industrial categories of Y2, Y3, Y10, and Y11, the transition probabilities of the regime 2 dominate that of regime 1. To conclude these findings, we see that, for industries of Y1, Y3, Y5, Y7, and Y8, the influence level of the ERU on the CVs is dominated by the weak-impact regime; those dominated by the strong-impact regime can be found in industries of Y2, Y4, and Y9. In addition, we find that, no matter which exporting level (Y11, Y12, or Y13), the effects of the ERU on the CVs are all dominated by the strong impact regime. The final finding should be addressed on the industries of (Y6) and (Y10), which shows that the impact level is undetermined since for both regimes, the impact coefficients are insignificant.
Specification tests

Based on Hamilton (1996), this paper further concerns the specification tests of the MS model. Four hypotheses testing considered are presented as follows:

\[
\begin{align*}
H_0^1 &: \alpha_1 = \alpha_2; \\
H_0^2 &: \beta_1 = \beta_2; \\
H_0^3 &: \sigma_1 = \sigma_2; \\
H_0^4 &: p_{11} = (1 - p_{22})
\end{align*}
\]

where the first three hypotheses are self-evident whereas the last one is to test for the transition probability. Under the null hypothesis,

\[
\text{Pr}(s_t = 1|s_{t-1} = 1) = \text{Pr}(s_t = 1|s_{t-1} = 2) = \text{Pr}(s_t = 1),
\]

the distribution of \( s_t \) is independent of \( s_{t-1} \).

The Wald test statistic for the above testing hypotheses are, respectively:

\[
\begin{align*}
\frac{(\hat{\alpha}_1 - \hat{\alpha}_2)^2}{\text{Var}(\hat{\alpha}_1) + \text{Var}(\hat{\alpha}_2) - 2\text{Cov}(\hat{\alpha}_1, \hat{\alpha}_2)} &\sim \chi^2(1) \\
\frac{(\hat{\beta}_1 - \hat{\beta}_2)^2}{\text{Var}(\hat{\beta}_1) + \text{Var}(\hat{\beta}_2) - 2\text{Cov}(\hat{\beta}_1, \hat{\beta}_2)} &\sim \chi^2(1) \\
\frac{(\hat{\sigma}_1 - \hat{\sigma}_2)^2}{\text{Var}(\hat{\sigma}_1) + \text{Var}(\hat{\sigma}_2) - 2\text{Cov}(\hat{\sigma}_1, \hat{\sigma}_2)} &\sim \chi^2(1) \\
\frac{[\hat{p}_{11} - (1 - \hat{p}_{22})]^2}{\text{Var}(\hat{p}_{11}) + \text{Var}(\hat{p}_{22}) - 2\text{Cov}(\hat{p}_{11}, \hat{p}_{22})} &\sim \chi^2(1)
\end{align*}
\]

As we observe from Table 4, the Wald statistics for the null of equality are mixed. From the viewpoint of whole Taiwan’s industries, it is hard to conclude that data are drawn from two different states since the null of no strong-weak impact switching can only be rejected for three industry categories of Y2, Y4, and Y7 at 5% significance level. However, the null of no drift switching of the MS model are all shown to be significant even at 1% level. This implies that if the MS model is appropriate, the ERU may not be the major factor but other factors, which could switch the CVs of Taiwan’s industries. Moreover, the model’s volatility influence can be shown by the values of the volatility coefficient. As we see from Table 4, the data of eight industries are shown to fit a two-state model when the volatility is stimulated.

From Table 4 again, under the null of the distribution of \( s_t, s_{t-1} \) is independent of \( s_{t-1} \), only six out of thirteen industries are rejected at 5% significance level. However, when based on the 10% level, one can reject the null of "no regime change," and then conclude that a two-state first-order MS model is appropriate for the "goodness of fit" analysis.

<Insert Table 4 about here>
VI. Concluding remark

Based on the controversies between more opportunities to achieve the corporate goals when exchange rates fluctuate and the harmful experiences of the large movements of exchange rates, this paper attempts to investigate the impacts of the ERU on the CVs for the industries concerned in Taiwan. A regime-switching regression is applied. To allow for variance to be drawn from different states, this paper extends the first-moment switching model to a second-moment one. In other words, we consider a MS model not only with a switching intercept and a switching slope, but with a switching error variance.

We first employ the traditional OLS approach and find that the ERU has the significantly positive impacts on the values among the industries of chemistry, electron, plastic and rubber, but has the negative impacts on that of food industry. However, the structural unstable phenomena from the CUSUM and CUSUM of squares tests during the estimation period reduce the explaining power of the ERU affecting the CVs when the OLS regression is applied.

Two different regimes of a strong-impact and a weak-impact are identified by the values of impact coefficients. For industries of chemistry, food, electricity, plastic, and rubber, the influence level of the ERU on the CVs is dominated by the weak impact regime; those dominated by the strong impact regime are found in the industries of electron, glass, and steel. We also find that the effects of the ERU on the CVs are all dominated by the strong impact regime for all three export ratio levels (over 50%, under 30%, or between 30% and 50%). However, the industries of paper and textile show that the impact level is undetermined since, for both regimes, the impact coefficients are insignificant.

The Wald statistics for the null of equality are mixed. Even though the null of no drift switching is shown to be significant for all Taiwan’s industries, it is hard to conclude that data are drawn from two different states since the null of no strong-weak impact switching can only be rejected for three industry categories of electron, glass, and plastic. This implies that if the MS model is appropriate, the ERU may not be the major factor but other factors, which could switch the CVs of Taiwan’s industries. Nonetheless, for the model’s volatility influence, the data of eight industries are shown to fit a two-state model when the volatility is stimulated.

When testing for the transition probability, under the null of the distribution of $s_t | s_{t-1}$, only six out of thirteen industries are rejected at 5% significance level. However, when based on the 10% level, we are able to reject the null of "no regime change," and then conclude that a two-state first-order MS model is appropriate for the "goodness of fit" analysis.
Appendix

Consider a competitive and risk-neutral firm whose production function is the type of Cobb-Douglas function, \( Q_t = F(L_t, K_t) = A_t L_t^{\alpha} K_t^{1-\alpha} \), where \( L_t \) is the labor employed, \( K_t \) is the capital employed, and \( Q_t \) is the output produced. The subscript \( t \) denotes the time elapsed, \( A \) is the technical parameter, and \( \alpha \) and \( 1-\alpha \) are the output elasticity with respect to labor and capital, respectively. The representative competitive firm hires labor at the fixed money wages \( w \), and makes the gross investment by the adjustment of an increasing convex cost \( C(I_t) \) which is assumed to be \( C(I_t) = I_t^\beta \), \( \beta > 1 \). The firm makes export quotation as to the domestic output in terms of foreign currency \( P_t \), and then inverts it to be the home price \( p_t \) by ways of current exchanges rates \( e_t \), i.e., \( p_t = e_t P_t \).

Thus, the firm's earnings at time \( t \) can be represented as:

\[
C_t = \pi_t L_t^{\alpha} K_t^{1-\alpha} - wL_t - \gamma I_t^\beta
\]  

(A-1)

The objective of the firm is to maximize the expected present value of its cash flows subject to the capital accumulation function:

\[
\frac{dK_t}{K_t} = (I_t - \delta K_t)dt,
\]  

(A-2)

\( \delta \) is the constant depreciation rate, and the behavioral equation of the output price:

\[
\frac{dp_t}{p_t} = \sigma dZ
\]  

(A-3)

where \( dZ \) is a Wiener process with mean zero and unit variance. Equation (A-3) specifies the price process that describes the output prices uncertainty in terms of the home currency that is transmitted by the exchange rate uncertainty, and captures the following properties:

\[
E_t(\pi_s) = \pi_t, s \geq t \text{ and } \text{Var}(p_s/\pi_t) = (s - t) \sigma^2.
\]

The value function of the firm can be written as the function of the two state variables \((K_t, \pi_t)\):

\[
V(K_t, \pi_t) = \max_{I_t, L_t} E_t \left[ \int_0^\infty \left[ \pi_s L_s^{\alpha} K_s^{1-\alpha} - wL_s - \gamma I_s^\beta \right] e^{-r(s-t)} ds \right]
\]  

(A-4)

where \( r \) is the constant discount rate. The optimality condition for maximizing equation (A-4) requires that the total returns required by the firm equal the total returns expected by the firm, that is, the following identity equation holds:

\[
rV(K_t, \pi_t) dt = \max_{I_t, L_t} \left[ \pi_t L_t^{\alpha} K_t^{1-\alpha} - wL_t - \gamma I_t^\beta \right] dt + E_t(dV)
\]  

(A-5)

where the term at the right-hand side of equation (A-5) is the total returns required by the firm, and the terms at the left-hand side of equation (A-5) are the total returns.
expected by the firm which consists of the cash flows and the expected capital gain or loss $E_t(dV)$. We apply Ito’s Lemma to calculate the capital gain or loss $(dV)$:

$$dV = V_K dK + V_\pi d\pi + \frac{1}{2} V_{KK} (dK)^2 + \frac{1}{2} V_{\pi\pi} (d\pi)^2 + V_{\pi K} (d\pi)(dK)$$  \hspace{1cm} (A-6)

Substituting equations (A-2) and (A-3) into equation (A-6), we get the expected change in the value of the firm given $E_t(dZ) = (dt)^2 = (dt)(dZ) = 0$:

$$E_t(dV) = [(I_t - \delta K_t)V_K + \frac{1}{2} \pi^2 \sigma^2 V_{\pi\pi}] dt$$  \hspace{1cm} (A-7)

Again substituting equation (A-7) into equation (A-5), we obtain:

$$rV(K_t, \pi_t) = \max_{I_t, L_t} [\pi_t L_t^{\alpha} K_t^{1-\alpha} - w L_t - \beta \gamma - (I_t - \delta K_t)V_K + \frac{1}{2} \pi^2 \sigma^2 V_{\pi\pi} ]$$  \hspace{1cm} (A-8)

From equation (A-8), we can show that:

$$\max_{I_t} [\pi_t L_t^{\alpha} K_t^{1-\alpha} - w L_t] = \tau \pi_t^{1/\alpha} K_t$$  \hspace{1cm} (A-9)

where $\tau = (1 - \alpha) \alpha \beta \gamma$ and the term at the right-hand side of equation (A-9) is the marginal revenue product of capital (MRP). Differentiating the term at the right-hand side of equation (A-8) with respect to $I_t$ gives:

$$\nabla \cdot I_t^{\alpha} \nabla$$

that the condition for the optimal investment of the firm requires that the marginal investment cost equal the marginal value of capital. Further substituting equations (A-9) and (A-10) into equation (A-8) yields:

$$rV(K_t, \pi_t) = \tau \pi_t^{1/\alpha} K_t + (\beta - 1)\gamma \beta \gamma - \delta K_t V_K + \frac{1}{2} \pi^2 \sigma^2 V_{\pi\pi}$$  \hspace{1cm} (A-11)

Both equations (A-10) and (A-11) can be expressed as a non-linear second-order partial differential equation. Following Mussa (1977) and Abel (1983), we have imposed enough structure on the two equations to obtain a set of explicit solutions as follows:

$$V(K_t, \pi_t) = b_t K_t + \frac{(\beta - 1)\gamma (b_t / \beta_t)^{\beta - 1}}{r - \theta \sigma^2}$$  \hspace{1cm} (A-12)

where $b_t = \frac{\tau \pi_t^{1/\alpha}}{r + \delta - \alpha \sigma^2 / 2(1 - \alpha)^2}$, $\theta = \frac{\beta(1 - \alpha + \alpha \beta)}{2(1 - \alpha)^2 (\beta - 1)^2}$

$$I_t = \left(\frac{b_t}{\beta_t}\right)^{\beta - 1}$$  \hspace{1cm} (A-13)
In equation (A-12), the value of the firm $V(K_t, \pi_t) > 0$ means requiring $r > \theta \sigma^2$. Since $b_t$ in equation (A-12) represents the present value of the expected marginal revenue product of capital, $b_t$, for all $t$ is greater than zero and $\theta$ in equation (A-13) is also greater than zero.

Partially differentiating $b_t$ in equation (A-13) with respect to $\sigma^2$, and differentiating $I_t$ in equation (A-14) with respect to $b_t$, we obtain:

$$\frac{\partial b_t}{\partial \sigma^2} = \frac{\tau \pi_t^{1-\sigma} \left[ -\frac{\alpha}{2(1-\alpha)^2} \right]}{\left[ r + \delta - \frac{\alpha \sigma^2}{2(1-\alpha)^2} \right]^2} > 0$$  \hspace{1cm} (A-15)

$$\frac{dI_t}{db_t} = \frac{1}{\beta \gamma (\beta - 1)} \left( \frac{b_t}{\beta \gamma} \right)^{2-\beta} > 0$$  \hspace{1cm} (A-16)

where an increase in $\sigma^2$ in equation (A-15) denotes an increase in the uncertainty of exchange rates. Further differentiating $V_t$ in equation (A-12) with respect to $\sigma^2$, we get:

$$\frac{\partial V(K_t, \pi_t)}{\partial \sigma^2} = K_t \frac{\partial b_t}{\partial \sigma^2} + \frac{(r - \theta \sigma^2)(\frac{b_t}{\beta \gamma})^{\frac{1}{\beta - 1}} \frac{\partial b_t}{\partial \sigma^2} + \frac{(\beta - 1)\theta}{\beta \gamma} \left( \frac{b_t}{\beta \gamma} \right)^{\frac{1}{\beta - 1}}}{(r - \theta \sigma^2)^2}$$  \hspace{1cm} (A-17)

From equation (A-17), we know that, since $\partial b_t / \partial \sigma^2 > 0$ in equation (A-15) and $dI_t / db_t > 0$ in equation (A-16), $\partial V(K_t, \pi_t) / \partial \sigma^2 > 0$, which means that an increase in the exchange rate uncertainty would lead to an increase in the present value of the expected earnings of the firm if the marginal revenue product of capital is the strictly convex function of the domestic output prices, $\theta > 1$, and discount rate is large enough, i.e., $r > \theta \sigma^2$. Of course, if $r < \theta \sigma^2$, then the above result will not hold; that is, the uncertainty of exchange rates affecting the corporate values is rather ambiguous.
References:


Engel, C., and J. D. Hamilton (1990), "Long Swings in the Dollar: Are They in the Data and do Markets Know it?", *American Economic Review*, 80, 689-713.


Pozo, S. (1992), "Conditional Exchange-Rate Volatility and the Volume of


### Table 1 GARCH (1,1) modeling for the exchange rate volatility

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>Estimator</th>
<th>S.D.</th>
<th>Z-statistic</th>
<th>P-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \alpha_0 )</td>
<td>0.0205</td>
<td>0.0081</td>
<td>2.5444</td>
<td>0.0109</td>
</tr>
<tr>
<td>( \alpha_1 )</td>
<td>0.6313</td>
<td>0.1422</td>
<td>4.4385</td>
<td>0.0001</td>
</tr>
<tr>
<td>( \beta_1 )</td>
<td>0.3545</td>
<td>0.1069</td>
<td>3.3138</td>
<td>0.0009</td>
</tr>
</tbody>
</table>

### Table 2 OLS estimation

<table>
<thead>
<tr>
<th>( \hat{\alpha} )</th>
<th>( \hat{\beta} )</th>
<th>( R^2 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.214*</td>
<td>0.062*</td>
<td>0.1382</td>
</tr>
<tr>
<td>0.488*</td>
<td>0.283*</td>
<td>0.0385</td>
</tr>
<tr>
<td>0.351*</td>
<td>-0.030*</td>
<td>0.002</td>
</tr>
<tr>
<td>0.343*</td>
<td>0.002</td>
<td>0.007</td>
</tr>
<tr>
<td>0.473*</td>
<td>0.027</td>
<td>0.027</td>
</tr>
<tr>
<td>0.546*</td>
<td>0.057*</td>
<td>0.028</td>
</tr>
<tr>
<td>0.0951*</td>
<td>0.011</td>
<td>0.011</td>
</tr>
<tr>
<td>0.206*</td>
<td>0.023</td>
<td>0.023</td>
</tr>
<tr>
<td>1.011*</td>
<td>0.212*</td>
<td>0.212*</td>
</tr>
<tr>
<td>0.350*</td>
<td>0.057*</td>
<td>0.057*</td>
</tr>
<tr>
<td>0.343*</td>
<td>0.058*</td>
<td>0.058*</td>
</tr>
</tbody>
</table>

### Table 3. Maximum likelihood estimates for state-transition estimation of Markov switching

<table>
<thead>
<tr>
<th>Parameters</th>
<th>( \alpha_1 )</th>
<th>( \alpha_2 )</th>
<th>( \beta_1 )</th>
<th>( \beta_2 )</th>
<th>( \sigma_1 )</th>
<th>( \sigma_2 )</th>
<th>( p_{11} )</th>
<th>( p_{22} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>RX to Y1</td>
<td>0.173</td>
<td>0.292</td>
<td>-0.029</td>
<td>0.021</td>
<td>0.029</td>
<td>0.031</td>
<td>0.993</td>
<td>0.992</td>
</tr>
<tr>
<td>RX to Y2</td>
<td>0.256</td>
<td>0.717</td>
<td>0.034</td>
<td>0.151</td>
<td>0.023</td>
<td>0.253</td>
<td>0.992</td>
<td>0.993</td>
</tr>
<tr>
<td>RX to Y3</td>
<td>0.246</td>
<td>0.365</td>
<td>0.014</td>
<td>0.039</td>
<td>0.024</td>
<td>0.046</td>
<td>0.872</td>
<td>0.963</td>
</tr>
</tbody>
</table>

* indicates significant at the 5% critical value.
Note: 1 The numbers in the parentheses are the values of $t$-statistic.
2. *, ** and *** denote significant at 1%, 5% and 10% level, respectively.
3. The 1%, 5%, and 10% significant level of $t$-statistics are 2.61, 2.35, and 1.98, respectively.

Table 4. Specification tests

<table>
<thead>
<tr>
<th>Null hypothesis</th>
<th>$H^1_0$: $\alpha_1 = \alpha_2$</th>
<th>$H^2_0$: $\beta_1 = \beta_2$</th>
<th>$H^3_0$: $\sigma_1 = \sigma_2$</th>
<th>$H^4_0$: $\rho_{11} = \rho_{22}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>RX to Y1</td>
<td>368.3</td>
<td>3.391***</td>
<td>0.3387</td>
<td>3.729***</td>
</tr>
<tr>
<td>RX to Y2</td>
<td>214.6</td>
<td>5.707**</td>
<td>127.9</td>
<td>3.717***</td>
</tr>
<tr>
<td>RX to Y3</td>
<td>233.5</td>
<td>0.5437</td>
<td>18.21</td>
<td>5.255**</td>
</tr>
<tr>
<td>RX to Y4</td>
<td>214.6</td>
<td>5.707**</td>
<td>127.9</td>
<td>3.717***</td>
</tr>
<tr>
<td>RX to Y5</td>
<td>132.9</td>
<td>0.02467</td>
<td>1.833</td>
<td>3.507***</td>
</tr>
<tr>
<td>RX to Y6</td>
<td>135.5</td>
<td>0.5179</td>
<td>5.539</td>
<td>3.707***</td>
</tr>
<tr>
<td>RX to Y7</td>
<td>227.3</td>
<td>7.341</td>
<td>1.059</td>
<td>6.531**</td>
</tr>
<tr>
<td>RX to Y8</td>
<td>347.9</td>
<td>0.3069</td>
<td>0.603</td>
<td>4.022**</td>
</tr>
<tr>
<td>RX to Y9</td>
<td>111.5</td>
<td>0.5566</td>
<td>36.43</td>
<td>3.308***</td>
</tr>
<tr>
<td>RX to Y10</td>
<td>12.79</td>
<td>0.4701</td>
<td>26.59</td>
<td>4.126**</td>
</tr>
<tr>
<td>RX to Y11</td>
<td>197.4</td>
<td>3.466</td>
<td>3.740</td>
<td>3.740***</td>
</tr>
<tr>
<td>RX to Y12</td>
<td>70.03</td>
<td>1.560</td>
<td>19.37</td>
<td>4.152***</td>
</tr>
<tr>
<td>RX to Y13</td>
<td>119.6</td>
<td>0.484</td>
<td>36.06</td>
<td>3.354***</td>
</tr>
</tbody>
</table>

Note: 1 The number is the Wald statistic
2. *, ** and *** denote significant at 1%, 5% and 10% level, respectively.
3. The 1%, 5%, and 10% significant level of $\chi^2(1)$ are 6.63, 3.84, and 2.72, respectively.
Figure-1 the exchange rate movement of NTD/USD

Figure-2  GARCH (1,1) modeling for the exchange rate volatility

Figure-3.1 Plot of Y1 against RX  Figure-3.2 Plot of Y2 against RX

Figure-3.3 Plot of Y3 against RX  Figure-3.4 Plot of Y4 against RX

Figure-3.5 Plot of Y5 against RX  Figure-3.6 Plot of Y6 against RX

Figure-3.7 Plot of Y7 against RX  Figure-3.8 Plot of Y8 against RX
Figure-3.9 Plot of Y9 against RX

Figure-3.10 Plot of Y10 against RX

Figure-3.11 Plot of Y11 against RX

Figure-3.12 Plot of Y12 against RX

Figure-3.13 Plot of Y13 against RX

Figure-3 The plots of the CUSUM and CUSUM of Square
Figure-3.13 RX and Y13

Figure-4: The diagrams of the inferred probabilities for industries’ states