“The relationship between stock returns and foreign exchange rates in China using smooth regime-switching approach”

AUTHORS	Chien-Jen Wang Po-Chin Wu Huei-Hsieh Lin

ARTICLE INFO	Chien-Jen Wang, Po-Chin Wu and Huei-Hsieh Lin (2013). The relationship between stock returns and foreign exchange rates in China using smooth regime-switching approach. *Investment Management and Financial Innovations*, *10*(3)
RELEASED ON	Thursday, 03 October 2013
JOURNAL	"Investment Management and Financial Innovations"
FOUNDER	LLC “Consulting Publishing Company “Business Perspectives”

NUMBER OF REFERENCES	NUMBER OF FIGURES	NUMBER OF TABLES
0	0	0

Chien-Jen Wang (Taiwan), Po-Chin Wu (Taiwan), Huei-Hsieh Lin (Taiwan)

The relationship between stock returns and foreign exchange rates in China using smooth regime-switching approach

Abstract

This paper applies the STARX (Smooth Transition Autoregressive with Exogenous Transition) models to investigate whether exchange rates and stock market returns has the nonlinear relationship. Data from Chinese Shanghai and Shenzhen stock markets are employed to demonstrate our result. It is found that the nonlinear Logistic STARX model exhibits superior forecasting performance on both stock markets. With the proposed constructed nonlinear equation, market investors and government policymakers can directly and easily apply available past exchange rates data to measure the impact of exchange rates on China's stock returns. The arbitrage regions and exchange rate exposures are also provided to enhance the risk premium.

Keywords: regime-switching, STARX model, exchange rate exposure, arbitrage region.
JEL Classification: F31, C32.

Introduction

With the continuing globalization and internationalization of financial markets, the interdependence of transnational financial markets is getting stronger. Therefore, the embedded volatility of a specific country's financial market may straightforwardly affect the stability of other international financial markets. The exchange rate, the most important price indicator in a foreign exchange market, has profound impacts on a country's international trade and economic growth. For those export-oriented countries, exchange rate uncertainty highly influences a company's revenue, earnings, and stock price via changes in exports' relative prices, thereby disturbing the performance of a country's stock market. The relationship between exchange rates and stock returns is a vital issue for the global financial markets.

In discussions on the relationship between exchange rates and the stock prices, classical theorems have mainly been differentiated into two main models: the flow-oriented models (Dornbusch and Fischer, 1980) and the stock-oriented models (Branson, 1983; Frankel, 1983). The former stress how exchange rate movement will affect trade balance and the real income and stock price of a firm. The latter emphasize how exchange rates are determined by the demand and supply of capital assets − stocks and bonds. The two theorems both assume that there exists an implicit relationship between exchange rates and stock prices. Additionally, numerous empirical studies have found that the importance of exchange rates cannot be neglected in the analysis of capital markets (Fama, 1981; Cornell, 1983; Chen, Roll and Ross, 1986; Ajayi and Mougoue, 1996; Katechos, 2011). For example, in an examination of eight industrial countries, Solnik (1987) found a negative relationship between exchange rate movements and domestic stock returns. Ma and Kao (1990), investigating six countries, found that domestic currency appreciation negatively affected domestic stock price for the export-dominant country. Many empirical works have also confirmed this relationship between foreign exchange rates and stock returns (Choi, 1995; Chow, Lee and Solt, 1997; Bartram, Dufey and Frenkel, 2005).

Empirical literature employing econometric methods to investigate the relationship between exchange rates and capital returns can be divided into the linearity and nonlinearity schools of thought. Using a linear model, Jorion (1990) found that only 5% of the U.S. multinational companies had significant foreign exchange rate exposure (i.e., the effect of exchange rate on stock prices) in the period of 1971-1987. Choi and Prasad (1995) found a similar low exchange rate exposure ratio for the U.S. multinational companies. However, some literature on non-U.S. companies had slightly higher exchange rate exposure ratios (Maysami and Koh, 2000; Kiymaz, 2003).

The linear model seems to demonstrate less significant exchange rate exposure, and some researchers have, therefore, argued that this phenomenon may be derived from past literature's neglect of the nonlinear and asymmetric adjustment of stock returns. There is some evidence that traditional linear models may be inappropriate to investigate the relationship between exchange rates and stock returns. For example, the inefficiency of financial markets, the existence of transaction costs and heterogeneous and risk-averse investors, the disturbance of political and economic policy, and specific financial crises usually cause nonlinear adjustment of economic variables in different regimes (Michael, Nobay and Peel, 1997; Kanas, 2005). Therefore, some theoretical literature has tried to employ nonlinear models to investigate the nonlinear relationship between exchange rates and

firm values (Krugman, 1987; Marston, 1990; Marston, 2001; Priestley and Odegaard, 2007). Lei and Kling (2006) found that, after the financial crash in late 2007, China's stock market restricted market activities and reduced liquidity; however, this did not prevent nonlinear changes to China's stock market returns. Ahmed, Rosser and Jamshed (2010) used the Markov regime-switching model to analyze stock market returns in 27 emerging market economies during the period of 1990-2006; the empirical results reveal that many such markets reject the absence of nonlinearities because of the presence of speculative bubbles. Senyuz, Yoldas and Baycan (2010) modeled Turkish business cycles and growth cycles using Markov switching models, which determined a three-state specification with different mean and variance dynamics for output growth and stock returns.

Up to now, there have been a number of econometric methods proposed to investigate the nonlinearity of relative economic variables, including Chaos Theory (Lorenz, 1963), the Artificial Neural Network (Minsky and Papert, 1969), the Markov Switching (MS) model (Hamilton, 1989), the Threshold Autoregressive (TAR) model (Tong, 1978), and the Smooth Transition Autoregressive (STAR) model. In essence, the Threshold Autoregressive (TAR) model and the Markov Switching (MS) model also are the regime-switching models; however, the switching process of the time series variable in two models is radical and discrete, which scarcely satisfies its actual movement, especially for low-frequency data (e.g., quarterly or yearly data) (Tong and Lim, 1980; Henneke, Rachev, Fabozzi and Nkiolov, 2011). In contrast, the STAR model, first proposed by Terasvirta and Anderson (1992), has at least two advantages when empirically applied. First, it allows for the smooth transition of relative economic variables rather than discrete switching between regimes, and can endogenously estimate transition parameter and transition speed. Second, it can evaluate the different marginal effects of the exchange rate on stock returns in different regimes and can help market investors construct an arbitrage region. In other words, stock price moves within an equilibrium band; once the price deviates sufficiently from the equilibrium, arbitrage trading takes place. Similar to the STAR model, the Smooth Transition Autoregressive with Exogenous Transition (STARX) model, first applied by McMillan (2001), employs as explanatory variables lagged exogenous variables rather than lagged dependent variables to reveal the nonlinear smooth switching process of dependent variables. McMillan indicated that stock market returns and macroeconomic variables indeed gave rise to a nonlinear relationship. Terasvirta, Dijk and Medeiros (2005) verified that STARX models can capture the nonlinear adjustment of economic variables within different regimes and have better forecasting performance than the TAR and MS models.

Although previous studies have extensively applied the STAR and STARX models to analyze the dynamic adjustment process of macroeconomic variables, the treatment in their empirical results is still inadequate. First, they did not clearly provide arbitrage regions for market investors to formulate proper investment strategies. Second and more importantly, they cannot distinguish the differential effects of exchange rates on stock returns as lagged stock returns in different regimes. This will give rise to an inaccurate basis for investment decision and government policy. Finally, most studies focused on the developed countries, while developing countries were not fully examined.

In the last decade, China's economy and capital market have opened up gradually and grown quickly. According to statistics from the International Monetary Fund (IMF), China's gross domestic product (GDP) surpassed Japan's in 2010 Q2, making China the second-largest economic entity in the world. Since China's international competition and capital market continue to expand, the impact of Chinese yuan (RMB) exchange rates on stock markets, and the possibility of structural change in China's transition economy have become critical issues.

In July 2005, China changed its RMB exchange rate policy for the first time. The pre-July 2005 exchange rate regime was mainly pegged to the U.S. dollar, whereas the new exchange rate regime is pegged to a basket of currencies and has formalized an adjustable and flexible exchange rate mechanism system[1]. Compared to the past, the volatility of RMB exchange rates has increased, implying that it is now more difficult for investors to forecast the changing tendency of the Chinese yuan. Due to the more flexible movement of Chinese yuan exchange rates, the influence of the RMB exchange rate on capital markets has attracted much research attention.

In this article, the STARX models have smoothly dynamic regime-switching process, and the nonlinear estimation results will generate more accurate predictability. Based on the advantages of employing STARX models to describe the dynamic adjustment process of economic variables, the rapid growth of stock markets, and the transformation of the exchange rate mechanism in China, this paper applies the STARX (Logistic STARX or Exponential STARX) models to investigate whether the relationship between exchange rates and stock market returns in China is nonlinear and whether structural

[1] In July 2005, the People's Bank of China (PBC or PBOC) announced that it would begin to float an adjustable Chinese yuan exchange rate system based on market supply and demand, and pegged to a basket of currencies.

changes in stock market returns in China have occurred. In performing this empirical estimation, we choose the Chinese Shanghai and Shenzhen stock markets as sample cases.

The main contributions of this paper can be summarized as follows. First, we verify that China's stock markets (both the Shanghai and Shenzhen stock markets) fitted by the nonlinear Logistic STARX model do exhibit smooth change structurally and the marginal effects of lagged exchange rates on stock market returns are various in different regimes. Second, we provide the arbitrage regions of China's stock markets for investors. For example, when the Shanghai A stock index is above 4,000 points or below 1,200 points, investors can obtain a risk premium from investing in the market. Third, employing past available information (i.e., lagged exchange rates), market investors can easily forecast future stock indexes and adopt appropriate investment strategies; this is not possible using traditional linear models with the current exchange rate as an explanatory variable. Finally, to sustain the exchange rate in a specified target zone, a country's central bank usually intervenes in the foreign exchange market, which further influences the stock market. Therefore, employing the estimation results of our constructed STARX models, a central bank can assess the effects of intervening in the exchange rate on stock returns. Overall, our estimated STARX model is confirmed to satisfy the appropriateness, convenience, and availability necessary for empirical applications, and can evaluate the impact of exchange rates on stock returns. It also has useful policy implications.

The remainder of this paper is organized as follows. Section 1 presents the empirical model and methodologies. Section 2 describes the data and the empirical results. The last section concludes.

1. Empirical model

This study employs the concepts of nonlinearity and smooth transition emphasized in the STARX model to establish the nonlinear equation for the empirical estimation in China's stock markets, and to evaluate the smooth switching characteristics of stock returns and the lagged effect of exchange rates on stock returns.

To perform the empirical study we follow Terasvirta's (1994) estimation procedures of nonlinearity. First, a linear regression model is specified and estimated. Second, an auxiliary regression is constructed for testing the nonlinearity of relevant variable and choosing the optimal lag-length of transition variable. Third, using a sequence of nested hypothesis testing we can choose a model between the Logistic STARX (LSTARX) and the Exponential STARX (ESTARX) for proceeding with nonlinear estimation.

1.1. Linear regression model. To apply STARX models to evaluate the relationship between exchange rates and stock returns, we need first to construct the linear regression model in which the dependent variable is stock returns and the explanatory variables are the lagged exchange rates, i.e.,

$$S_{i,t} = \eta_0 + \sum_{i1=1}^{m} \alpha_{i1} ER_{t-i1} + \varepsilon_{i,t}, \tag{1}$$

where $S_{i,t}$ is the stock market returns that include the return rates of the indices of China's Shanghai A Stock, Shanghai B Stock, Shenzhen A Stock, and Shenzhen B Stock. ER_{t-i1} ($i1$ = 1,2, …, m) represents the lagged Chinese yuan exchange rates (RMB/USD). The estimated effects of RMB exchange rates on stock market returns are represented by α_{i1}. $\varepsilon_{i,t}$ is a residual.

1.2. Smooth regime switching model. Once the linear regression model has been specified, the nonlinear STARX model can be constructed as equation (2).

$$\begin{aligned} S_{i,t} &= \eta_0 + \sum_{i1=1}^{m1} \alpha_{i1} ER_{t-i1} + \\ &+ (\eta_1 + \sum_{i1=1}^{m1} \beta_{i1} ER_{t-i1}) F(S_{t-d}, \gamma, C) + \varepsilon_t, \end{aligned} \tag{2}$$

where η_0 and η_1 are the intercepts in different regimes, respectively. α_{i1} and β_{i1} show the estimated coefficients in different regimes. The lag lengths, m_1 = 1,2,…,6, are chosen by the Akaike information criterion (Akaike, 1974). $F(S_{t-d},\gamma,C)$ is the transition function with value in the interval [0,1], being either a logistic or an exponential process as displayed in equations (3) and (4), respectively. γ denotes the smooth parameter, interpreting the transition speed of stock market returns between different regimes. C stands for the transition point of the transition variable. S_{t-d} is the transition variable with the optimal lag period d; d = 1, 2, …, 6 is estimated and chosen through the linearity test as shown in equation (5).

$$F(S_{t-d}, \gamma, \mathrm{C}) = \{1 + \exp[-\gamma(S_{t-d} - C)]\}^{-1}, \tag{3}$$

$$F(S_{t-d}, \gamma, \mathrm{C}) = \{1 - \exp[-\gamma(S_{t-d} - C)^2]\}. \tag{4}$$

Logistic transition function (equation (3)) permits the smooth transition in stock price with positive or negative return. Exponential transition function (equation (4)) identifies the behavior of larger or smaller returns, and then captures the market depth and the effect of transaction costs on traders' behavior[1].

[1] To determine the role of transaction costs in the functioning of financial markets, Cipriani and Guarino (2008) analyzed the effects of transaction costs in financial markets and highlighted the negative effect of transaction costs on the process of price discovery. Forbs (2003) argued that security transaction taxes as transaction costs can reduce excessive trading and volatility as well as prevent the occurrence of financial crises.

1.3. Linearity test and transition function selection. To further investigate whether the stock returns in China follow a nonlinear smooth switching process this paper first estimates the auxiliary regression equation (5), and then decides the optimal lag-length d of transition variable S_{t-d} using the F-test.

$$v_t = \eta_0 + \sum_{j=1}^{J} (\eta_{1j}\pi_{t-j} + \eta_{2j}\pi_{t-j}S_{t-d} + \eta_{3j}\pi_{t-j}S_{t-d}^2 + \eta_{4j}\pi_{t-j}S_{t-d}^3) + \xi_t$$

$$H_0 : \eta_{2j} = \eta_{3j} = \eta_{4j} = 0, \tag{5}$$

where v_t is the residual of linear model in equation (1); π_{t-j} means the explanatory variables of linear model in equation (1); η_0 represents intercept term; $\eta_{1j} \sim \eta_{4j}$ denote estimated parameters. We proceed with F-test from lagged-one period to lagged-six period. As the F-test rejects H_0, the estimation equation is a nonlinear form as shown in equation (2); otherwise, a linear form holds. On determining the optimal lag-length (d), Tsay (1989) proposed to use the maximum value of the F-statistic or the minimum value of p. If d is accurately chosen, then the auxiliary regression can be viewed as appropriate under the nonlinear model; otherwise, the auxiliary regression model is probably misspecified. Moreover, the residuals were considered to be free from serial autocorrelation to prevent model misspecification and also to obtain more parsimonious models.

Once the function form is decided, we can further proceed with the choice of transition function. During the investigation process, according to the nested sequence test proposed by Terasvirta (1994), we use F-statistic to test from equations (6) to (8), and choose the good-fitting type of transition function, whether it is a logistic or an exponential form.

$$H_{04} : \eta_{4j} = 0 \tag{6}$$

$$H_{03} : \eta_{3j} = 0 \mid \eta_{4j} = 0 \tag{7}$$

$$H_{02} : \eta_{2j} = 0 \mid \eta_{3j} = \eta_{4j} = 0 \tag{8}$$

If the test result rejects H_{04}, the good-fitting model is LSTARX. If rejecting H_{03} and accepting H_{04}, the model belongs to ESTARX. If rejecting H_{02} and accepting H_{03} and H_{04}, the model belongs to LSTARX.

1.4. Arbitrage region and exchange rate expo-sure. Employing the estimation results of equation (2) we can further construct the arbitrage region and the exchange rate exposure of China's stock markets. Assuming that the good-fitting model is a LSTARX one, we can write the estimated equation as equation (9).

$$\hat{S}_t = \eta_0 + \sum_{i1=1}^{m1} \alpha_{i1} ER_{t-i1} + (\eta_1 + \sum_{i1=1}^{m1} \beta_{t-i1} ER_{t-i1}) \times \{1 + \exp[-\gamma(S_{t-d} - \hat{C})]\}^{-1}, \tag{9}$$

where the transition function can be shown as equation (10).

$$F(S_{t-d}) = \{1 + \exp[-\gamma(S_{t-d} - \hat{C})]\}^{-1} \tag{10}$$

The estimated transition parameter, $\hat{C}$, shows the intermediate point between ascending and descending stock market returns. This interpretation is direct from the fact that as stock market return $S_{t-d} = \hat{C}$, then $F(.) = 1/2$ As stock market return $S_{t-d} \geq \hat{C}$, then $F(.) = 1$; stock market return locates at the upper regime, and the exposure coefficient of exchange rate is $\left(\sum_{i1}^{m1} \alpha_{i1} + \sum_{i1}^{m1} \beta_{i1}\right)$. Contrarily, as $S_{t-d} \leq \hat{C}$, then $F(.) = 0$; stock market return locates at the lower regime, and the exposure coefficient of exchange rate is $\left(\sum_{i1}^{m1} \alpha_{i1}\right)$.

2. Empirical results

2.1. Data description. Recently, many efforts have been made to study China's volatile stock markets. China has stock markets in both Shanghai and Shenzhen. To perform the empirical estimation, we choose China's four main stock markets, i.e., Shanghai A Stock, Shanghai B Stock, Shenzhen A Stock, and Shenzhen B Stock, as sample[1]. Furthermore, RMB/USD exchange rates are chosen as the target exchange rates to investigate the impact of Chinese yuan exchange rates on stock market returns (S_t)[2]. The sample period spans from 2005:7M, the announcement date of the new exchange rate regime in China, to 2010:3M. Data source is the Taiwan Economic Journal (TEJ).

Table 1 shows the descriptive statistics of all variables. Regarding volatility of stock market, Shanghai B Stock is much more volatile than Shanghai A Stock (the standard deviations were 0.54 and 0.46, respectively). However, the volatility of Shenzhen B Stock has less volatile than Shenzhen A Stock (the standard deviations were 0.42 and 0.55, respectively). The probable reason is that the main transaction currency is different in the B stock

[1] In both the Shanghai and Shenzhen stock markets, the market participants of A Stock are mainly Chinese domestic investors, whereas the participants of B Stock include foreign investors outside China.

[2] The results of a correlation coefficient test between stock returns and four foreign currencies (USD, EUR, JPY, and TWD) indicate that the RMB/USD rate exhibits the highest correlated coefficient with China's stock markets. Therefore, we choose the RMB/USD rate as the target exchange rate. Relevant data will be provided upon request.

markets (Shanghai B uses the U.S. dollar; Shenzhen B uses the H.K. dollar). In addition, Shenzhen B exhibits comparatively lower transaction volumes than Shenzhen A, whereas Shanghai B and Shanghai A are the opposite; this may be another source of the different volatility results.

Table 1. Descriptive statistics

Variable	SHANGHAI A	SHANGHAI B	SHENZHEN A	SHENZHEN B	RMB/USD
Mean	7.8592	5.0663	6.5925	6.0204	7.3785
Std. dev.	0.4668	0.5446	0.5545	0.4255	0.5175
Max	8.7410	5.9420	7.3840	6.6770	8.1056
Min	7.0380	4.0720	5.5690	5.2430	6.8228
Skew	-0.1372	-0.2114	-0.3957	-0.2003	0.1357
Kurt	2.1181	1.8977	1.8566	1.7584	1.3017
J-B	2.0259 [0.3631]	3.3102 [0.1910]	4.5928 [0.1006]	4.0421 [0.1325]	7.0248 [0.0298]

Note: Summary statistics of Chinese Yuan Exchange Rates and China four stock market index returns during 2005:7M to 2010:3M. J-B represents the statistic of Jarque-Bera normal distribution test. The digit in brackets is *p*-value.

Figure 1(e) depicts the time series of the RMB/USD exchange rates. It is obvious that the Chinese yuan exchange rates were continually rising from 2005 to 2009. This reflects the fact that in the wake of the global financial crisis, China's government energetically encouraged traders to export so as to earn large quantities of foreign exchange, which served to move the yuan exchange rates still higher.

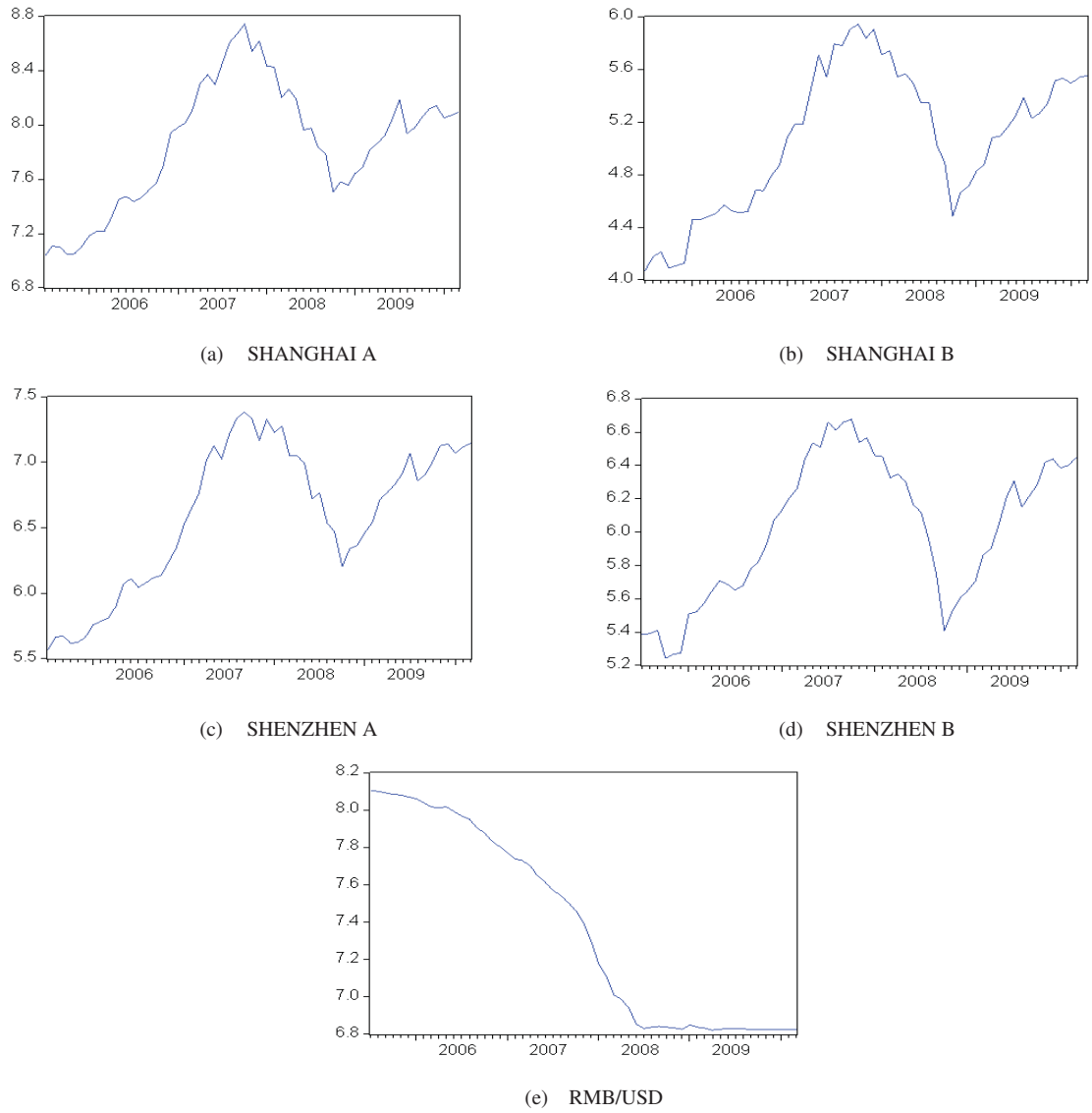

Fig. 1. Times series of China's stock market returns and Chinese yuan exchange rates

2.2. Estimation result of linear model. Table 2 shows the estimation results of stock market returns employing linear models with lagged exchange rates. The one- and four-period lagged exchange rates display strong statistical significance, and their estimated coefficients exhibit a consistent direction in China's four stock markets. However, the one- and four-period lagged exchange rates have the opposite impact on stock market returns. The probable reason for this consequence is the existence of a *J*-curve effect. According to the *J*-curve effect, the increase in the RMB exchange rate will correspond at first to more costly imports and less valuable exports in China, leading to a bigger initial deficit or smaller surplus. However, due to the competitive, relatively low-priced exports, China's exports will begin to increase. Local consumers will also purchase less of the more expensive imports and focus on local goods. China's trade balance will eventually improve to better levels compared to the pre-devaluation period, which will further stimulate China's economic growth and stock returns. Thus, the signs of the estimated coefficients in one- and four-period lagged exchange rates are negative and positive, respectively.

Table 2. Estimation of stock market returns: linear model with lagged exchange rates

	SHANGHAI A	SHANGHAI B	SHENZHEN A	SHENZHEN B
C	10.090*** (14.200)	8.182*** (10.145)	10.696*** (13.606)	7.686*** (10.848)
ER_{t-1}	-3.022*** (-4.787)	-3.411*** (-4.761)	-2.997*** (-4.292)	-2.448*** (-3.890)
ER_{t-4}	2.699*** (4.374)	2.967*** (4.236)	2.425*** (3.551)	2.206*** (3.585)
Adj. R^2	0.336	0.366	0.414	0.235
AIC	0.787	1.040	0.989	0.781
SIC	0.899	1.152	1.101	0.893
F-stat.	14.188 [0.000]	16.053 [0.000]	19.419 [0.000]	8.999 [0.000]

Notes: Sample period is 2005:7M to 2010:3M. The digits in parentheses and brackets are *t*-statistics and *p*-value, respectively. Estimated equation is equation (1). *, **, *** stand for significance at 10%, 5%, and 1%, respectively.

2.3. Estimation result of STARX model. Once the linear models have been estimated as shown in Table 2, we can further use the *F*-test to estimate the auxiliary regression in equation (5) and select the optimal lag-length *d* of transition variable S_{t-d}. Table 3 shows the results of the linearity test. Evidently the optimal lag-length with the maximum *F*-statistic value in these four stock markets is one period.

Table 3. Linearity test

Variable	*d*					
	1	2	3	4	5	6
SHANGHAI A	79.419* [0.000]	37.199 [0.000]	29.924 [0.000]	26.404 [0.000]	16.175 [0.000]	9.531 [0.000]
SHANGHAI B	62.077* [0.000]	34.490 [0.000]	23.892 [0.000]	17.365 [0.000]	10.744 [0.000]	6.012 [0.000]
SHENZHEN A	79.643* [0.000]	41.194 [0.000]	26.601 [0.000]	17.996 [0.000]	10.047 [0.000]	5.590 [0.0003]
SHENZHEN B	105.251* [0.000]	44.617 [0.000]	26.907 [0.000]	17.744 [0.000]	11.077 [0.000]	7.013 [0.000]

Notes: *d* is the lagged period of transition variable. The digits in the table and bracket are *F*-statistic and *p*-value, respectively. * denotes the optimal lagged period with maximum *F*-statistic (or minimum *p*-value) to reject linearity hypothesis. Estimated equation is equation (5).

The estimation results of nonlinear STARX model are shown Table 4. It is interesting to find the good-fitting nonlinear model for China's markets is a Logistic STARX form. That is, after the period of China's new exchange rate regime, it seems improper employing the traditional linear regression model to forecast stock market returns. From the smooth parameter (γ) we know that Shanghai B and Shenzhen B Stocks have higher transition speed than Shanghai A and Shenzhen A Stocks. This result might signify that B Stocks are probably open to foreign investors, and the effect of their capitals flowing in and out results in more activity and volatility than A Stocks.

Table 4. Estimation of stock market returns: STARX model

Good-Fit Model	SHANGHAI A LSTARX	SHANGHAI B LSTARX	SHENZHEN A LSTARX	SHENZHEN B LSTARX
η_0	11.592*** (6.293)	7.990*** (7.747)	8.777*** (3.852)	7.671*** (8.717)
ER_{t-1}	-2.299 (-1.260)	-2.985* (-1.391)	-0.629 (-0.211)	-2.668* (-1.353)
ER_{t-4}	1.693 (0.950)	2.515 (1.199)	0.195 (0.067)	2.374 (1.235)
η_1	-11.023** (-2.542)	-8.602*** (-4.291)	-6.636* (-1.816)	-5.817*** (-2.952)
ER_{t-1}	4.471* (1.445)	4.297* (1.770)	2.306 (0.635)	4.532* (1.659)
ER_{t-4}	-2.732 (-0.992)	-2.947 (-1.260)	-1.133 (-0.328)	-3.569* (-1.378)
γ	1.043**	2.236***	1.304**	1.755**
C	7.860***	4.998***	6.313***	6.019***
d	1	1	1	1
Adj. R^2	0.876	0.825	0.865	0.757
AIC	-1.588	-1.112	-1.460	-1.682
SIC	-1.291	-0.815	-1.162	-1.385

Notes: Estimated equations are equations (2), (3), and (4). Sample period is 2005:7M to 2010:3M. The digits in parentheses are *t*-statistics. *, **, *** stand for significance at 10%, 5%, and 1%, respectively.

Since the nonlinear estimation results are superiors to the linear ones, we further evaluate the arbitrage regions and the exchange rate exposure of China's stock markets. Take Shanghai A Stock as the example, the model describing its dynamic adjustment process from Table 4 is the Logistic STARX model and can be rewritten as follows:

$$\begin{aligned}\hat{S}_t &= 11.59 - 2.29ER_{t-1} + 1.69ER_{t-4} + \\ &+ (-11.02 + 4.47ER_{t-1} - 2.73ER_{t-4}) \times \\ &\times \{1 + \exp[-1.04(S_{t-1} - 7.86)]\}^{-1},\end{aligned} \tag{11}$$

where $F(S_{t-1}) = \{1 + \exp[-1.04(S_{t-1} - 7.86)]\}^{-1}$ is the transition function. The estimated transition parameter, $\hat{C}$ (=7.86), shows the intermediate point between rising and falling stock prices. This interpretation derives directly from the fact that as stock market return S_{t-1} = 7.86, then $F(.)$ = 1/2. The estimated smooth parameter, $\hat{\gamma}$ (=1.04), suggests a moderate transition from one regime to the other. In equation (11), as stock market return $S_{t-1} \geq 7.86$, then $F(.) = 1$. The stock market return is located in the upper regime and moves in accordance with the following equation:

$$\hat{S}_t = 0.57 + 2.18ER_{t-1} + 1.04ER_{t-4}. \tag{12}$$

Contrarily, as $S_{t-1} \leq 7.86$, then $F(.) = 0$. The stock market return is located in the lower regime and moves in accordance with the following equation:

$$\hat{S}_t = 11.59 - 2.29ER_{t-1} + 1.69ER_{t-4}. \tag{13}$$

Moreover, from the estimated transition function the investors can construct the arbitrage regions of stock market return as $S_{t-1} \leq 6.82$ (estimated stock index is about 1,200 points) in the bearish market or $S_{t-1} \geq 8.90$ (estimated stock index is about 4,000 points) in the bullish market.

Finally, based on equations (12) and (13) we can further assess the exchange rate exposure of Shanghai A Stock market returns, i.e., identifying the effects of exchange rate movements on stock returns. When stock market return $S_{t-1} \geq 7.86$, the exposure coefficient of exchange rate is 3.22 (= 2.18 + 1.04). Contrarily, as $S_{t-1} \leq 7.86$, then the exposure coefficient of exchange rate is -0.6 (= −2.29 + 1.69). Evidently, the exchange rate exposures of China's Shanghai A Stock market are different as one-period lagged stock return located in different regimes. For example, as the Shanghai A Stock market located in the stage of bearish market, the depreciation of RMB is unfavorable to the investors in stock market due to negative coefficient of exchange rate exposure. Therefore, without considering of the asymmetry and nonlinearity of the stock returns, the differential exchange rate exposures may be ignored. This is one important contribution of our paper, and is neglected in previous relevant studies.

Conclusions

In an incomplete stock market, to induce risk-averse investors to invest in the market, some risk premium would be required to compensate for the probable risks they face. Kanas (2005) noted that traditional arbitrage theory regards risk premium as an arbitrage gain that implies the nonlinearity in asset return dynamics. In addition, structural changes in asset returns may also occur as the firms involved make obvious adjustments based on the external economic environment and public policy. As China's economy

opens up and grows rapidly, the Chinese yuan continues to appreciate. For China's changing capital markets, it would undoubtedly be mismodeling to utilize a traditional linear model for estimation. This is why the viewpoint of nonlinearity has continuously been emphasized, and why empirical studies increasingly tend to focus on employing nonlinear models to estimate economic and financial variables.

This paper constructs smooth transition regime-switching models with lagged Chinese yuan exchange rates to investigate the impact of lagged exchange rates on the returns of China's four important stock markets. We find that the nonlinear Logistic STARX model can exhibit superior forecasting performance in both the Shanghai and Shenzhen stock markets. In addition, employing the constructed nonlinear equation, market investors and government policymakers can directly and easily apply available past exchange rates data to measure the impact of exchange rates on China's stock returns. This paper also provides the arbitrage regions and exchange rate exposures for investors to enhance the risk premium. For example, in the Shanghai A, when the stock index is higher than 4,000 points in a bullish market or lower than 1,200 points in a bearish market, investors can construct an arbitrage region to obtain extra risk premium. Regarding the exchange rate exposure of RMB, we also find that the exchange rate exposures of China's stock markets are different as lagged stock returns in different regimes. For example, the coefficient of exchange rate exposure is positive as the Shanghai A Stock market index locates in a high region, and negative as the index locates in a low region.

Compared with stock markets in other countries, China's stock markets are still in the nascent stages of development. However, with the infusion of more foreign capitals into the country, China's stock markets will assume an important role in the international asset portfolio in the future. It is imperative, therefore, that the government has comprehensive investment policies in place. Our study provides new results that market investors with proper investment strategies and the government with accurate policy-making to perform risk control management in advance.

References

1. Ahmed, E., Rosser, J.B. Jr., Y.U. Jamshed (2010). Emerging Markets and Stock Market Bubbles: Nonlinear Speculation? *Emerging Markets Finance and Trade*, 46 (4), pp. 23-40.
2. Ajayi, A.R., M. Mougoue (1996). On the Dynamic Relation between Stock Prices and Exchange Rates, *Journal of Financial Research*, 19 (2), pp. 193-207.
3. Akaike, H. (1974). A New Look at the Statistical Model Identification, *IEEE Transactions in Automatic Control*, AC-19, pp. 716-723.
4. Bartram, S.M., Dufey, G., M.R. Frenkel (2005). A Primer on the Exposure of Non-financial Corporations to Foreign Exchange Rate Risk, *Journal of Multinational Financial Management*, 15, pp. 394-413.
5. Branson, W.H. (1983). Macroeconomic Determinants of Real Exchange Risk, in R.J. Herring (ed.), Managing Foreign Exchange Risk, Cambridge University Press, Cambridge, MA.
6. Chen, N.F., Roll, R., S. Ross (1986). Economic Forces and the Stock Market, *Journal of Business*, 59, pp. 383-403.
7. Choi, J.J. (1995). The Japanese and US Stock Prices: A Comparative Fundamental Analysis, *Japan and the World Economy*, 7, pp. 347-360.
8. Choi, J.J. A.M. Prasad (1995). Exchange Risk Sensitivity and its Determinants: a Firm and Industry Analysis of U.S. Multinationals, *Financial Management*, 24, pp. 77-88.
9. Chow, E.H., Lee, W.Y., M.E. Solt (1997). The Exchange-Rate Risk Exposure of Asset Returns, *Journal of Business*, 70 (1), pp. 105-123.
10. Cipriani, M., A. Guarino (2008). Transaction Costs and Informational Cascades in Financial Markets, *Journal of Economic Behavior and Organization*, 68 (3), pp. 581-592.
11. Cornell, B. (1983). The Money Supply Announcement Puzzle: Review and Interpretation, *American Economic Review*, 73, pp. 644-657.
12. Dornbusch, R., S. Fischer (1980). Exchange Rates and the Current Account, *American Economic Review*, 70 (5), pp. 960-971.
13. Fama, E. (1981). Stock Returns, Real Activity, Inflation, and Money, *American Economic Review*, 71, pp. 545-565.
14. Forbes, K. (2003). Comment on Securities Transaction Taxes and Financial Markets, *IMF Staff Papers*, 50 (Special Issue), pp. 181-186.
15. Frankel, J. (1983) A. Monetary and Portfolio-Balance Models of Exchange Rate Determination, in J.S. Bhandari & B.H. Putnam (eds.), Economic Interdependence and Flexible Exchange Rates, MIT Press, Cambridge, MA.
16. Hamilton, J.D. (1989). A New Approach to the Economic Analysis of Nonstationary Time Series and the Business Cycle, *Econometrica*, 57 (2), pp. 357-384.
17. Henneke, J., Rachev, S., Fabozzi, F., Nkiolov, M. (2011). MCMC Based Estimation of Markov Switching ARMA-GARCH Models, *Applied Economics*, 43 (3), pp. 259-271.
18. Jorion, P. (1990). The Exchange Rate Exposure of U.S. Multinationals, *Journal of Business*, 63, pp. 331-345.
19. Katechos, G. (2011). On the Relationship between Exchange Rates and Equity Returns: A New Approach, *Journal of International Financial Markets, Institutions and Money* (in Press).

20. Kanas, A. (2005). Nonlinearity in the Stock Price Dividend-Relation, *Journal of International Money and Finance*, 24, pp. 583-606.
21. Kiymaz, H. (2003). Estimation of Foreign Exchange Exposure: an Emerging Market Application, *Journal of Multinational Financial Management*, 13, pp. 71-84.
22. Krugman, P. (1987). Pricing to Market When the Exchange Rate Changes, In: Arndt, S., Richardson, J.D. (eds.), Real Financial Linkages among Open Economies, MIT Press, pp. 49-70.
23. Lei, G., G. Kling. (2006). Regulatory Changes and Market Liquidity in Chinese Stock Markets, *Emerging Markets Review*, 7(3), pp. 162-175.
24. Lorenz, E.N. (1963). Deterministic Nonperiodic Flow, *Journal of Atmospheric Science*, 20, pp. 130-141.
25. Ma, C.K., G.W. Kao (1990). On Exchange Rate Changes and Stock Price Reactions, *Journal of Business Finance and Accounting*, 17 (3), pp. 441-449.
26. Marston, R.C. (1990). Pricing to Market in Japanese Manufacturing, *Journal of International Economics*, 29, pp. 217-236.
27. Marston, R.C. (2001). The Effects of Industry Structure on Economic Exposure, *Journal of International Money and Finance*, 20, pp. 149-164.
28. Maysami, R.C., T.S. Koh (2000). A Vector Error Correction Model of the Singapore Stock Market, *International Review of Economics and Finance*, 9 (1), pp. 79-96.
29. McMillan, D.G. (2001). Nonlinear Predictability of Stock Market Returns: Evidence from Nonparametric and Threshold Models, *International Review of Economics and Finance*, 10, pp. 353-368.
30. Michael, P., Nobay, A.R., D.A. Peel (1997). Transaction Costs and Nonlinear Adjustment in Real Exchange Rates: An Empirical Investigation, *Journal of Political Economy*, 105, pp. 862-879.
31. Minsky, M., S. Papert (1969). *Perceptions: an Introduction to Computational Geometry*, MIT Press, Cambridge, MA.
32. Priestley, R., B.A. Odegaard (2007). Linear and Nonlinear Exchange Rate Exposure, *Journal of International Money and Finance*, 26, pp. 1016-1037.
33. Senyuz, Z., Yoldas, E., O. Baycan (2010). Regime-Switching Analysis of Turkish Business and Stock Market Cycles, 6th Colloquium on Modern Tools for Business Cycle Analysis: The Lessons from Global Economic Crisis, Eurostat, Luxembourg.
34. Solnik, B. (1987). Using Financial Prices to Test Exchange Rate Models: A Note, *Journal of Finance*, 42, pp. 141-149.
35. Terasvirta, T. (1994). Specification, Estimation and Evaluation of Smooth Transition Autoregressive Models, *Journal of the American Statistical Association*, 89, pp. 208-218.
36. Terasvirta, T., H.M. Anderson (1992). Characterizing Nonlinearities in Business Cycles Using Smooth Transition Autoregressive Models, *Journal of Applied Economics*, 7, pp. S119-S136.
37. Terasvirta, T., Dijk, D.V., M.C. Medeiros (2005). Linear Models, Smooth Transition Autoregressions, and Neural Networks for Forecasting Macroeconomic Time Series: A Re-examination, *International Journal of Forecasting*, 21, pp. 755-774.
38. Tong, H. (1978). On a Threshold Model, in Pattern Recognition and Signal Processing (C.H. Chen (ed.)), Amsterdam: Sijthoff and Noordhoff, pp. 101-141.
39. Tong, H., Lim, K.S. (1980). Threshold Autoregression, Limit Cycles and Cyclical Data, *Journal of Royal Statistics Society*, B42, pp. 245-292.
40. Tsay, R. (1989). Testing and Modeling Threshold Autoregressive Process, *Journal of the American Statistical Association*, 84, pp. 231-240.