Exchange Rate Volatility and Stock Returns in China: A Markov Switching SVAR Approach

Bo Tang *†
Department of Economics, University of Sheffield

Abstract

This study investigates the spillovers between exchange rate volatility and stock returns in the Chinese financial market. The multivariate vector autoregression (VAR) analysis demonstrates that only a unidirectional relationship exists running from stock returns to foreign exchange rates. Moreover, a conventional structural VAR (SVAR) has been introduced to test the structural innovations, but it is inadequate to interpret the shocks of interest. Fortunately, a Markov switching mechanism (MS) allows the coefficients and variances of the SVAR model to be state dependent, which clearly captures the volatile structures. The high (low) volatilities in the smoothed probabilities are consistent with the tough (tranquil) periods of the Chinese economy. A striking feature of the impulse response is that the Shanghai B-share index (SHBI) has positive effects for the stocks markets and negative impacts on the foreign exchange markets. Finally, this paper proposes possible practical implications for practitioners and investors that paying attention to the system risk from the RMB policy changes due to the increasing pressures from trade partners, which may alter the current unidirectional causalities in the Chinese financial market.

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Keywords: exchange rate volatility, stock returns, Markov switching SVAR

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†Correspondence: ecp12bt@sheffield.ac.uk. Bo Tang, Department of Economics, University of Sheffield, Edgar Allen House, 241 Glossop Road, Sheffield S10 2GW, UK. Tel: + 44 114 222 3398. Fax: + 44 114 222 3458

1 Introduction

The spillover in the financial market has been a research focus in the macroeconomic field for decades. The dynamic relationship between stock market and foreign exchange market is found to be bidirectional (Granger et al., 2000; Pan et al., 2007; Rjoub, 2012), or unidirectional (Kim, 2003; Lin, 2012), which can be the shocks running from exchange rates to stock prices or from stock prices to exchange rates. No long run relationship has also been proved in some empirical studies (Tabak, 2006; Ibrahim, 2000; Nieh and Yau, 2010). The spillover is much more evident during the financial crisis period (Granger et al., 2000; Fang, 2002).

Previous study on the Chinese financial market has suggested that foreign capital shares in the Chinese stock markets are not entirely segmented from global financial conditions (Bailey, 1994), and there may exist a bidirectional relationship (Zhao, 2010) or unidirectional causality (Nieh and Yau, 2010) between the stock markets and foreign exchange markets. However, Chinese stock markets constitute by RMB ordinary shares (known as A share) and foreign capital shares (known as B share). In addition, the shocks from Hong Kong stock market, in particular the Hang Seng Index (HSI), is a key indicator used by many practitioners and investors. So researches on the cross volatility between Chinese stock markets and foreign exchange markets should take all these indicators into consideration to have a fully exploration.

Differ from previous studies on the Chinese financial market, this study will investigate the causalities between exchange rate volatility and stock returns in a multivariate VAR approach. To get a preliminary impression of the structural shocks, a conventional SVAR will be conducted. Due to the inefficiencies of SVAR model, this paper will model the changes in volatility endogenously in a Markov switching mechanism(MS) based on the SVAR. Using daily data from both the stock markets and foreign exchange markets, three different samples, including the period of 1997 Asian financial crisis and 2008 global crisis , will be examined separately.

The remaining sections of this study is organised as follows. The empirical studies on the interactions between exchange rate volatility and stock returns are given in Section 2. Section 3 represents the data description and preliminary analysis. Section 4 illustrate the econometric models and the technical inferences. Empirical results are presented in Section 5 and last section concludes.

2 Exchange Rates Volatility and Stock Returns: the Empirical Literature

This study will review the literature on the exchange rate volatility and stock returns from the perspective of different economies[1]: emerging economies in which the Asian emerging economies during crisis will be discussed in detail since it is highly correlated with the Chinese economy, developed economies and the interplay between emerging economies and developed economies.

With the rising of emerging countries and increased openness of the world economy, the linkages between exchange rate volatility and stock returns in emerging markets have been studied from a broad perspective. Applying a Markov regime switching approach, Chkili and Nguyen (2013) represent that the stock markets have significant impacts on exchange rates in the BRICS countries, and a positive relationship has been found between exchange rate and stock returns in South African (Tovar-Silos and Shamim, 2013), while this is a regime dependent relationship and stock prices volatility dissymmetrically responses to the shocks in the currency market, that means the exchange rate volatility affects the transition probabilities across regimes (Walid et al., 2011). But bidirectional relations have been found between exchange rate and stock prices from the evidence of Turkey (Rjoub, 2012) and China (Zhao, 2010), and also a significant transmission shocks and volatility exits among these indicators (Turkyilmaz and Balibey, 2013). Asian emerging economies have received much attention with their increased influences in the Asia-Pacific region and in the world, in particular the 1997 Asian financial crisis period (Fang, 2002; Granger et al., 2000; Lin, 2012).

Changes in the foreign exchange market have become increasingly integrated with equity market in the world economies. Stock market in developed countries have a sophisticated regime and may withstand the shocks from currency market. However, existing studies have found the evidence of exchange rate risks on stock prices. Dominguez (2001) points out that exchange rates have signif-

[1] This study combines the classifications of emerging economies pursuant to the categories from International Monetary Fund (IMF)(16 July 2012) and the Emerging Market Global Players (EMGP) project at Columbia University (1 April 2013), as well as the list tracked by *The Economist*.

icant impact on the firm level and sectoral level stock prices in industrial countries. The impact between real exchange rate and stock prices(S&P 500) in the US is bidirectional in the short run (Bahmani-Oskooee and Sohrabian, 1992) but is negative running from real exchange rate to stock prices in the study of Kim (2003) and Choi et al. (1992)(before October 1979, but it became significantly positive after that). Contrasting with the study of Bahmani-Oskooee and Sohrabian (1992), no long run relationship between exchange rate and stock prices has been found in the G-7 countries (Nieh and Lee, 2002), only a short run correlation for one day exists in the German, Canadian and UK markets [2]. Moreover, Ma and Kao (1990) suggest that the currency appreciation has a negative impact on the domestic market in an export-dominant economy sine it weakens the export markets' competitiveness, while appreciated currency lower the import costs and produce a positive effect on the domestic stock market if it is an import-dominated economy.

The cross-market crisis gives the world an warning that each country should appropriately responds to the cross-market shocks and makes adjustments swiftly and accordingly. The currencies in emerging economies are subject to the spillovers from advanced financial markets, and the crisis happened in one emerging country may spread to the neighboring emerging economies. Coudert et al. (2011) conclude that the effect of the contagion from developed economies has been intensified during global financial crisis. The pegged US dollar currency policies in emerging countries result in the expansion of the financial turmoil at the outset. The evidence of cross-region interactions has been examined by (Phylaktis and Ravazzolo, 2005) as well. They claim that the positive link between foreign exchange and stock prices in the Pacific Basin economies is linked through the channel of US stock market, but the shocks from financial crisis to the long run interaction of these markets is temporal. Kubo (2012) suggest that the Asian stock markets and US stock market are integrated, and the interaction between Asian economies and the US has been intensified, particularly in the information technology sectors. While the US stock market is not affected by any macro shocks from Japan but asymmetrically responsive to national growth and interest rate(Mun, 2012).

All in all, previous studies on the comovement between exchange rate volatility and stock returns

[2]The one day correlation means the currency depreciation will drag down or stimulate the stock returns on the following day.

have three consequences. The most common evidence is the bidirectional relationship, which means that the exchange rates lead stock prices and the stock prices will lead exchange rates as well. The second evidence is the unidirectional relationship between exchange rates and stock returns. This kind of effect may run either from exchange rates to stock prices or from stock prices to exchange rates. Once incorporating the cross-border interactions into the system, spillovers are more likely to happen from advanced financial markets to emerging markets, and also the crisis in one country may spread to its neighbours. The third type of evidence is that there is no long run relationship between exchange rate volatility and stock returns. Moreover, the practical information for investors and shareholders is that the foreign exchange rate shocks are exogenous for those cross-listed firms, which have little effect on firms'values.

3 Data Description and Preliminary Analysis

Due to unavailability of daily exchange rates data before 1994, the sample of this study ranges from 1 January 1994 to 31 December 2012. The daily exchange rates of USD against RMB(USD/RMB) and HKD against RMB(HKD/RMB) were collected from State Administration of Foreign Exchange. Five stock indexes has been gathered, namely the Shanghai A-share Index(SHAI), Shanghai B-share Index(SHBI), Shenzhen A-share Index(SZAI), Shenzhen B-share Index(SZBI) and the Hang Seng Index(HSI). They can be exported from the Qianlong securities trading software and downloaded from NetEase company. SHAI and SZAI are RMB ordinary shares listed in Shanghai and Shenzhen Stock Exchange, respectively. SHBI and SZBI are foreign stock shares traded in USD and HKD, respectively. A brief glance of the exchange rate and stock indexes can be obtained from Figure 1.

Most studies express the exchange rate changes as the natural logarithms of division between two continuous closing values (Zhao, 2010; Walid et al., 2011). The exchange rate volatility ER_t^i and stock returns SR_t^j in this study are calculated from the following equation:

$$ER_t^i = ln\left(\frac{p_t^i}{p_{t-1}^i}\right) \qquad SR_t^j = ln\left(\frac{p_t^j}{p_{t-1}^j}\right) \tag{1}$$

Where p_t^i denotes the different foreign exchange rates(USD/RMB or HKD/RMB) at time t. p_t^j represents the stock indexes(j=1 to 5 for the SHAI, SHBI, SZAI, SZBI, HSI, respectively) at time t. Table 1 represents the descriptive statistics of exchange rate volatility and stock returns. An examination of unit roots of exchange rate volatility and stock returns are conducted by using the Augmented Dick Fuller (ADF) test (Dickey and Fuller, 1979) and Phillips-Perron(PP) test (Phillips and Perron, 1988). Table 2 reports the stationary test results. All statistics are significant at 1%level, which implies the stationarity of these series.

4 The Econometric Models

4.1 Theoretical Model and Conventional Structural VAR Model

Previous studies on the correlations between exchange rate volatility and stock returns are found to be bidirectional ($SR_t^j \Leftrightarrow ER_t^i$)(Pan et al., 2007; Rjoub, 2012), or unidirectional ($SR_t^j \Leftarrow ER_t^i$ or $SR_t^j \Rightarrow ER_t^i$) (Kim, 2003; Lin, 2012), or no long run equilibrium existence (Tabak, 2006; Nieh and Yau, 2010), that is $SR_t^j \neq ER_t^i$. Conventional econometric method wildly applied in examining the correlations is the bivariate Granger causality test (Pan et al., 2007). It is based on a bivariate VAR(BVAR) model:

$$ER_t = \sum_{j=1}^{m} \alpha_j ER_{t-j} + \sum_{j=1}^{n} \beta_j SR_{t-j} + \varepsilon_t \tag{2}$$

$$SR_t = \sum_{j=1}^{m} \gamma_j ER_{t-j} + \sum_{j=1}^{n} \eta_j SR_{t-j} + \mu_t \tag{3}$$

Stock returns fail to Grange-cause exchange rate volatility when β_j=0, and exchange rate volatility can not Grange-cause stock returns if γ_j=0. While in this study, the situations in the Chinese stock market are quite complicated due to the classification of foreign capital shares and RMB ordinary shares. Considering the reduced form a k -dimensional VAR model with pth lags (Lütkepohl, 2005):

$$y_t = Dd_t + A_1 y_{t-1} + \cdots + A_p y_{t-p} + u_t \tag{4}$$

Where $y_t = (y_{1t}, \cdot\cdot\cdot, y_{nt})'$ is a $n \times 1$ dimensional vector. D is the coefficient matrix of the deterministic components d_t. A_i are $k \times k$ coefficient matrices for $i = 1, \cdot\cdot\cdot, p$ and u is k-element vector of error terms. The causality test is relied on the Wald test of the lagged terms(shocks) in the matrices A_i. However, the standard VAR approach is subject to the unrestrict properties in the shocks. Further stronger assumptions which are more directly associated with the theory can be imposed by structural VAR(SVAR) model. To specify a SVAR, re-write equation (4) and incorporate additional contemporaneous endogenous shocks and simple error structure into each equation (Lütkepohl, 2005; Lanne et al., 2010), and the typical A-B model is expressed as:

$$Ay_t = D^s d_t + A_1^s y_{t-1} + ... + A_p^s y_{t-p} + B\varepsilon_t \tag{5}$$

In the equation, y_t is k-dimensional vector of endogenous variables. A(A is full rank),D^s,$A_i^s(i = 1 \sim p)$ and B are $k \times k$ structural form arguments matrices. ε_t is a k-dimensional identity covariance matrix vector of structural innovations, $\varepsilon_t\ (0, I_k)$. The matrix may be normalized as $\Sigma\varepsilon = I_k$. When $A = I_k$ and $B = I_k$, that is B-model and A-model, respectively. According to equation (4) and (5), $u_t = A^{-1}B\varepsilon_t$, and $\Sigma_u = A^{-1}BB'A^{-1'}$. Therefore, the model has $k(k+1)/2$ equations. Since both A and B have k^2 elements, so a minimum of $2k^2 - \frac{1}{2}k(k+1)$ restrictions are needed to be imposed to identify matrices A and B. Estimating a SVAR is directly minimising the negative of the log-likelihood:

$$lnL_c(A, B) = -\frac{KT}{2}ln(2\pi) + \frac{T}{2}ln|A|^2 - \frac{T}{2}ln|B|^2 - \frac{T}{2}tr(A'B'^{-1}B^{-1}A\tilde{\Sigma_u}) \tag{6}$$

The overidentification test of SVAR can be conducted in a Likelihood Ratio (LR) test: $LR = T(logdet(\tilde{\Sigma_u^r}) - logdet(\tilde{\Sigma_u}))$. Where $\tilde{\sum}_u$ is the reduced form of variance-covariance matrix and $\tilde{\sum}_u^r$ is the restricted structural form estimation. The SVAR model has to be identified through certain kinds of restrictions in the short run parameters or the long run autoregressive parameters. However, the statistical validity of these restrictions can not be tested and this kind of identification technique is usually insufficient to interpret the shocks of interest. In reality, no theoretical framework support the normality hypothesis and it is usually not necessary for asymptotic inference. Fortunately, the existence of various error covariance matrices across regimes in the structural shocks can be easily and exactly identified by a Markov Switching(MS) property in the regimes (Sims et al., 2008; Lanne et al., 2010; Herwartz and Luetkepohl, 2011).

4.2 SVAR Model with Different Volatility Regimes

In the MS-SVAR model, the distribution of error term u_t is assumed to depend on a Markov process s_t (Lanne and Lütkepohl, 2010; Lanne et al., 2010; Netsunajev, 2013). Where s_t is a discrete state process with $t = (0, \pm 1, \pm 2, ... \pm M)$ and the transition probabilities is: $p_{ij} = Pr(s_t = j|s_{t-1} = i), i, j = 1, ..., M$.

$$u_t|s_t \sim N(0, \Sigma_{s_t}) \tag{7}$$

Generally, the distribution of u_t conditional on s_t is assumed to be normal, but this is just for the convenience of setting up the likelihood function. Pseudo maximum likelihood(ML) estimators will be used once the conditional normality of $u_{t|s_t}$ does not hold. Hence, the normality assumption is not necessary for the shocks identification. The covariance Σ_{s_t} in equation (7) will vary across regimes (Lanne et al., 2010), and it is also consistent with the properties of statistical data. Take the two states as an example(M=2), $p = \begin{bmatrix} p_{00} & p_{01} \\ p_{10} & p_{11} \end{bmatrix}$. $P(s_t = 0|s_{t-1} = 0) = p_{00}$, so $P(s_t = 1|s_{t-1} = 0) = 1 - p_{00}$. $P(s_t = 1|s_{t-1} = 1) = p_{11}$, then $P(s_t = 0|s_{t-1} = 1) = 1 - p_{11}$. Hence, the unconditional probabilities $p(s_t = 0) = (1 - p_{11})/(2 - p_{11} - p_{22})$ and $p(s_t = 1) = 1 - p(s_t = 0)$. When it comes to M-states, the MS structure becomes a model with mixed normal disturbance terms, $u_t = \begin{cases} N(0, \Sigma_1) & (p_{11}) \\ \vdots & \vdots \\ N(0, \Sigma_m) & (p_m) \end{cases}$. The identification of structural shocks in the MS model is based on the assumption that only the variances of the shocks are orthogonal across states but there will be not effect on the impulse responses. In addition, temporary shocks will not change across all sample periods (Lanne et al., 2010). As the error term $\varepsilon_t = B_t^{-1}$ determines the structural shocks, so any restrictions on conventional SVAR inferred from theory models are testable and over-identified.

Rewrite the SVAR equation (5) as $A_0 y_{t-i} = F x_{t-i} + \varepsilon_t$, where F_i is coefficient matrices and x_{t-i}

is a vector of lagged variables. Sims et al. (2008) propose the Markov switching SVAR in a batesian form, but all matrices can be state dependent:

$$A(s_t)y_{t-i} = F(s_t)x_{t-i} + \Xi^{-1}(s_t)\varepsilon_t \tag{8}$$

Where Ξ is a diagonal matrix and s_t is defined as m states Markov process with transition matrix $Q = q_{i,j}$(the transition probabilities). Equation (8) allows all the matrices to switch in a markov process, and another two kinds of MS process are switching coefficients and variances respectively.

$$\Xi(s_t)A(s_t)y_{t-i} = \Xi(s_t)F(s_t)x_{t-i} + \varepsilon_t \tag{9}$$

$$Ay_{t-i} = Fx_{t-i} + \Xi^{-1}(s_t)\varepsilon_t \tag{10}$$

Maximum likelihood(ML) estimation is usually applied in the estimation of MS-SVAR, while pseudo ML estimation will proceed when the conditional normality distribution is not held. The log likelihood function for a M-state MS-VAR model:$logL_t = \sum_{t=1}^{T} logf(y_t|Y_{t-1})$, where $f(y_t|Y_{t-1} = \sum_{i=0}^{M} Pr(s_t = i|Y_{t-1})f(y_t|s_t = i, Y_{t-1})$. The (pseudo) conditional likelihood function is as follows:

$$f(y_t|s_t = i, Y_{t-1}) = (2\pi)^{-k/2}det(\Sigma_i)^{-1/2}exp(\frac{1}{2}u_t'\Sigma_i^{-1}u_t), i = 1, ..., M. \tag{11}$$

Where Y_{t-1} is a matrix with the past information up to time t. $\Sigma_1 = BB', \Sigma_i = B\Lambda_i B', i = 1, ..., M$. While during the estimation process, the number of states selection is important for MS-SVAR model analysis. Considering the changes in the states of stock returns(exchange rate volatility), two or three states are normally selected [3], but we have to test the validity from a statistical information perspective. Normally, the log likelihood statistic with Akaike Information Criteria(AIC) and Schwarz Criteria (SC) are reliable to determine the best MS model (Psaradakis and Spagnolo, 2006; Herwartz and Luetkepohl, 2011).

[3]The shocks to stock returns and exchange rate volatility can be positive, negative or no changes, and the volatility states should be selected accordingly.

5 Empirical Results

5.1 Multivariate Granger Causality Test

Table 3 reports the multivariate Granger causality test results in three panels. In general, the multivariate Granger causality test illustrates that there are no spillovers from RMB ordinary shares(SHAI and SZAI) to the foreign exchange market. It can be expressed as $SR_A \nRightarrow ER$, where the subscript A denotes the RMB ordinary shares. However, strong and significant impacts on both the foreign exchange markets and stock markets have been identified from the volatile returns of foreign capital shares, particularly the shocks from Shanghai foreign capital stock market, that is $SR_{SHBI} \Rightarrow ER$ and $SR_{SHBI} \Rightarrow SR$. The shocks from SZBI are not as much as those from SHBI as the evidence from Table 3, and it can be summarised that the SZBI has an important impact on the Shanghai stock market and the foreign exchange rate of HKD against RMB. That is $SR_{SZBI} \Rightarrow SR_{Shanghai}$ and $SR_{SZBI} \Rightarrow ER_{HKD/RMB}$. After 1997 Asian financial crisis and the return of Hong Kong, the HSI has been observed close correlations with the Shanghai stock market, but it will not affect the exchange rate fluctuation of HKD/RMB. Finally, both foreign exchange markets do not exhibit any shocks to the stock market($ER \nRightarrow SR$), but changes in the USD/RMB have been identified a strong shock on the HKD/RMB($ER_{USD/RMB} \Rightarrow ER_{HKD/RMB}$).

5.2 A Parsimonious Conventional SVAR Analysis

The most tricky technique issue of SVAR approach is imposing restrictions on the variance-covariance matrix. A triangular Cholesky decomposition which makes all the elements above the diagonal matrix restricted as zero just identifies the SVAR. However, which parameter should be imposed as zero? Can be really counterintuitive. This study will follow the idea of Sims (1986) to derive the restriction options based on the theory assumption. Pursuant to equation (5) and its derivatives on the structural shocks, the restrictions on SVAR in this study are briefed in equation (12).

$$\begin{bmatrix} 1 & a_{12} & a_{13} & a_{14} & a_{15} & a_{16} & a_{17} \\ a_{21} & 1 & 0 & a_{24} & a_{25} & a_{26} & 0 \\ 0 & 0 & 1 & 0 & a_{35} & a_{36} & 0 \\ a_{41} & 0 & a_{43} & 1 & 0 & a_{46} & a_{47} \\ 0 & 0 & 0 & a_{54} & 1 & a_{56} & 0 \\ 0 & a_{62} & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & a_{74} & 0 & a_{76} & 1 \end{bmatrix} \begin{bmatrix} u_t^{SHAI} \\ u_t^{SHBI} \\ u_t^{SZAI} \\ u_t^{SZBI} \\ u_t^{HSI} \\ u_t^{USD/RMB} \\ u_t^{HKD/RMB} \end{bmatrix} = \begin{bmatrix} \varepsilon_t^{SHAI} \\ \varepsilon_t^{SHBI} \\ \varepsilon_t^{SZAI} \\ \varepsilon_t^{SZBI} \\ \varepsilon_t^{HSI} \\ \varepsilon_t^{USD/RMB} \\ \varepsilon_t^{HKD/RMB} \end{bmatrix} \quad (12)$$

The first equation indicates the stock returns of SHAI responding to the shocks from other stock markets (SHBI, SZAI, SZBI and HSI) and foreign exchange markets (USD/RMB and HKD/RMB). As the Shanghai stock market is really sensitive to external shocks, this study assumes that all the structural innovations have contemporaneous impact on SHAI. Other equations have a zero restriction meaning no structural innovations from those indexes. Lag selection of the conventional SVAR model is based on the information criteria, which is the same lag length (1 lag) as selected in the multivariate Granger causality test. The proposed restrictions in equation (12) has been imposed on the short run parameters, the estimation results indicate the over identification of the SVAR model. However, the χ^2 statistic of likelihood ratio(LR) test of identifying restrictions can not completely reject the null hypothesis. The χ^2 statistic equals 4.7 with a p-value 0.095, which partially accept the null. It means that the short run restrictions in equation (12) are still valid in the SVAR model. However, most structural impulse response figures (not reported) have a long duration with high uncertainties in the estimated short run parameters. The conventional SVAR model just partially rejects the null of overidentification as demonstrated in above analysis, which leads to the failure in the interpretation of shocks of interest in the impulse response graphs.

5.3 Empirical Analysis from SVAR with Markov Switching in Volatility

5.3.1 Model Selection and Prior Specifications

This study start the MS model with one lag in the VAR as demonstrated in previous sections. One lag is enough to ensure the stability of the VAR model based on the daily data. Another option about the MS model is the restrictions which can be imposed on the state dependent variance-covariance matrices. The states selection in this study starts from 2 states, then subsequently increase states and change restrictions. Table 4 reports the log likelihood statistics and information criteria of different MS models. The unrestricted VAR and SVAR model do not suggest any good indications in the model selection process. The MS-SVAR model can be easily implemented in Dyanre based on the Matlab platform. As it is illustrated in the table, panel A prefers the 3 states MS model with switching in the variance. Panel B indicates that the 2 states with coefficients switching in the MS model is suitable, and panel C demonstrates that 3 states with switching in the variance in B matrix is appropriate based on the sample of post world crisis.

The prior for the SVAR parameters is the six hyperparameters proposed by Sims and Zha (1998)[4]. Each element of the diagonal matrix $\xi^2(s_t)$ has been a gamma distribution prior and the parameters are set as $\bar{\alpha} = 1$ and $\bar{\beta} = 1$ in Gamma(α, β) (Sims et al., 2008). The last prior on transition matrix Q is a Dirichlet distribution proposed by Sims, Waggoner and Zha (2008), which has unrestricted parameters $\alpha_{i,j}$ and restricted parameters β_{ij}. In the transition matrix Q, all the off-diagonal elements are set as one and diagonal elements are computed with $\alpha_{jj} = \frac{p_{j,dur(h-1)}}{1-p_{j,dur}}$. Where $p_{j,dur}$ is the average duration in the markov chain.

5.3.2 Volatility Structure and Impulse Response Analysis

In the MS-SVAR model, the volatility structure is clearly demonstrated in the Markov chain with transition probabilities and the impulse response graphs. The transition probabilities among states are reported in Figure 5. It is clear that each state has a high probabilities in the ongoing state, which is illustrated by the diagonal elements of each matrix. The probabilities of state transformation between state 1 and state 2 are very low, especially the transfer from high volatility to low volatility. It is possible that the low volatility can move to a transition state (state 3), and vice versa, but the state transformation between high volatility (state 1) and transition volatility (state 3) will never happen in this case.

[4]Following Sims and Zha (2006), the prior specifications in this study are $\mu_1 = 0.57, \mu_2 = 0.13, \mu_3 = 0.1, \mu_4 = 1.2, \mu_5 = 10$ and $\mu_6 = 10$.

Figure 2, Figure 3 and Figure 4 illustrate the smoothed state probabilities for three different sample tests respectively. Each MS-SVAR model has different switching states, referred as distressed state, normal state and transition state [5]. In Figure 2, three states depicted from the whole sample test capture the volatilities in the foreign exchange markets and stock markets. The top part of Figure 2 integrates the Markov process of the three state-dependent variances, which looks full of volatility across the sample period. The remaining three parts of Figure 2 are the separated states with shaded areas during the high volatility periods which allow us to have a clear impression on these structures. State 1 is the normal state and it captures the tranquil periods on the markets following middle 2006 to early 2008, and late 2010 to late 2012. State 2 indicates the distressed state(high volatility state) which clearly represents the periods of bear market (middle 1995 to early 1996, May 1997 to May 1999, middle 2001 to middle 2005, 2008-2009 world crisis) and bull market (middle 1999 to middle 2001). State 3 displays the transition state which also indicates the vulnerable and volatile market across the period of 1997 Asian financial crisis and 2008 world crisis. Figure 3 depicts the smoothed probabilities for the subsample test of July 1997 to the end of 2007. Distressed states can be demonstrated from the high volatility in the middle 1997 and the late 2007. The separated state 1 illustrates the high volatility since middle 1997 to middle 1999, although several tranquil periods appeared during this period. Another significant character in state 1 was the distressed time in the late 2007. While state 2 captures several tranquil periods and the longest one started from middle 2001 to late 2006. Figure 4 represents the smoothed probabilities for 2008 world crisis and post crisis period. High volatility in state 1 indicates the distressed time in 2008, middle 2010 and around second quarter of 2011. State 2 captures the normal state from late 2008 to middle 2010. State 3 is the transition state, capturing several transition periods from middle 2010 to early 2011 and from middle 2011 to late 2012.

The impulse responses to the structural innovations for the three sample tests are presented in Figure 5-7. The shock with parameter uncertainties exactly identify the shocks from stock market and foreign exchange rate market. In the whole sample test, SHAI shock has positive effects for SZAI

[5] The economic activity and financial turbulence usually have normal regime and distressed regime two categories Davig and Hakkio (2010), but some studies may have more than two regimes, so the stepwise regime name can be given, for example, the transition regime(between the normal regime and distressed regime).

and itself, and negative effects on SHBI and foreign exchange rate of USD/RMB can be identified from SHAI shock. However, the shocks on SZBI, HSI and HKD/RMB are difficult to ascertain as the impulse response shock with confidence intervals across the zero line. SHBI shock clearly represents positive impacts on stock markets and negative effects for foreign exchange markets. SZAI is negatively correlated with SHAI, SHBI and foreign exchange rate of HKD/RMB, but it exhibits positive effects to the stock returns in the Shenzhen stock market. SZBI has negative effects for foreign capital shares but its influences on other indexes are still ambiguous because of the uncertainty of the parameters. With the strengthened economic ties between Hong Kong and mainland China, Shanghai and Shenzhen stock market usually receive strong shocks from Hong Kong market(the HSI). One of the significant shocks is the spillover on SHBI. The variation of USD/RMB also has a negative impact on SHBI, but positive effects have been identified on the foreign exchange market. Last column of Figure 5 sketches the HKD/RMB shock, which gives the ambiguous effects as well.

The impulse responses of stock markets and foreign exchange markets shocks for the subsample test from July 1997 to the end of 2007 are not quite different with those results from the whole sample test. However, it is obvious that the duration of parameter uncertainties of these shocks last much longer than those from in Figure 5, in particular the shocks from foreign capital shares, Shenzhen stock market and exchange rate of USD/RMB. Finally, the results from subperiod of January 2008 to December demonstrates that the shock directions and durations are similar with the whole sample test results. But on the whole, the impulse responses from two subsample tests show significant evidence in the parameter uncertainty which clearly reflects the shocks from regional and global crisis.

6 Conclusions

Motivated from the turmoil in the foreign exchange market and stock market in China due to my personal working experience in the financial institute, this study empirically investigates the spillovers between exchange rate volatility and stock returns in China over the sample period of 1 January 1994 to 31 December 2012. Different from previous studies mainly in three aspects: (1) this paper explores the evidence from both the foreign capital shares(Shanghai B share and Shenzhen B share) and RMB ordinary shares(Shanghai A share and Shenzhen A share) listed in the Shanghai and Shenzhen stock exchange, as well as the correlations from Hong Kong stock market(Hang Seng Index, HSI), and the corresponding shocks from the foreign exchange markets of USD/RMB and HKD/RMB. While previous studies on Chinese stock market neither covered both the foreign capital shares and RMB ordinary shares into their analyses simultaneously, nor took the Hong Kong market into consideration (Nieh and Yau, 2010; Tian and Ma, 2010; Zhao, 2010); (2)the 1997 Asian financial crisis and 2008 world crisis have been examined as vital shocks to the financial market in plenty of studies, but previous studies on Chinese stock market did not investigate the causalities during these periods; and (3) this study applies a multivariate VAR to explore the dynamic relations between exchange rate volatility and stock returns, and tests the contemporary shocks in a conventional SVAR model, and then extends the model in a Markov structure in the volatility, which exactly captures the volatilities in the Chinese financial markets.

Based on a multivariate Granger causality test, interactions between foreign exchange markets and stock markets do not indicate bidirectional relations (see Table 3). It demonstrates that RMB ordinary shares do not have any impact on the foreign exchange market($SR_A \nRightarrow ER$), but the spillovers from Shanghai B shares index(SHBI) to other Chinese stock markets and foreign exchange markets are very significant($SR_{SHBI} \Rightarrow ER$ and $SR_{SHBI} \Rightarrow SR$). Although foreign capital shares are traded in HKD in the Shenzhen stock market, it has been found a significant shock on the Shanghai stock market($SR_{SZBI} \Rightarrow SR_{Shanghai}$) and the foreign exchange rate of HKD/RMB also suffers from the shocks of SZBI($SR_{SZBI} \Rightarrow ER_{HKD/RMB}$). Moreover, HSI is proved to affect the Shanghai stock market but does not show any significant impact on the foreign exchange rates. However, the volatility of foreign exchange markets do not Granger cause the changes in stock returns($ER \nRightarrow SR$) based on the Wald test and only a shock on the HKD/RMB has been found from the USD/RMB($ER_{USD/RMB} \Rightarrow ER_{HKD/RMB}$).

A conventional SVAR analysis is followed the multivariate Granger causality test. The short run restrictions in equation (12) are based on some theoretical assumptions and practical experiences, which partially rejects the null hypothesis of overidentification. But the statistical validity of these short run restrictions can not be examined and the identification is usually inadequate to explain certain shocks of interest.

Fortunately, the Markov switching SVAR allows the variances and coefficients to be state dependent, which clearly captures the spillovers between stock markets and foreign exchange markets. Smoothed state probabilities from each panel indicate the distressed state, normal state and transition state of Chinese financial market (see Figure 2-4). The high(low) volatilities are consistent with the tough(tranquil) periods of the Chinese economy. While the transition state implies the instabilities of the other two states. Impulse response of MS-SVAR models indicate that SHBI shocks have positive effects on the stock markets and negative impact on the foreign exchange markets. The remaining shocks from stock markets(SHAI, SZAI, SZBI and HSI) or foreign exchange markets (USD/RMB and HKD/RMB) have effects for one or another, but most effects are ambiguous due to the high parameter uncertainties across the zero line. However, the shocks of the parameters are more uncertain in the sample of 1997 Asian financial crisis.

To conclude, this study investigates the spillovers between exchange rate volatility and stock returns in the Chinese financial market. The empirical findings indicates that only unidirectional relationship from stock markets to foreign exchange market exists and the fluctuations of foreign exchange rates do not Granger cause stock returns. This may be due to the managed RMB policy. In addition, with the ongoing openness of Chinese economy and the inflow of foreign capital in the Chinese stock market, in particular the Shanghai B share, shocks from SHBI have significant impact on the stock markets and foreign exchange market. Investors investing in RMB ordinary shares and foreign exchange markets (USD/RMB and HKD/RMB) can make appropriate adjustments pursuant to the fluctuations of barometer of SHBI. However, Chinese authorities are facing pressures from international community to appreciate RMB and allow RMB to be more flexible and tradable in the foreign exchange market, this may bring system risk to the stock market and change the current unidirectional causalities.

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Table 1: Preliminary statistics

Panel A: Descriptive statistics for exchange rate volatility	Mean	Std.Dev	Skewness	Kurtosis	Normality	Q(36)
USD/RMB	0.0000	0.0006	-8.3541	262.1573	11130***	142.56***
HKD/RMB	0.0000	0.0007	-2.2688	78.7551	31398***	103.81***
Panel B: Descriptive statistics for stock returns						
SHAI	0.0002	0.0204	1.4403	27.428	10461***	114.61***
SHBI	0.0001	0.0213	0.1361	5.2011	2073.3***	127.62***
SZAI	0.0003	0.0209	0.6177	14.768	6984.2***	80.906***
SZBI	0.0002	0.0215	0.0756	6.3514	2749.8***	78.501***
HSI	0.0001	0.0170	0.0672	9.2621	4485.4***	65.134***

Notes:

1. The exchange rate volatility and stock returns were calculated according to equation 1.
2. *** denotes the statistic rejects the null hypothesis at 1% level.
3. The normality test reported by Ox programming language is based on Doornik and Hansen(1994) [6]. They argue that the JB test(Jarque and Bera,1987) has poor small sample properties and the skewness and kurtosis are not independently distributed, also the speed of sample kurtosis closes to normality very slow. Doornik and Hansen define the test statistic as: $e_2 = z_1^2 + z_2^2 \sim \chi^2(2)$. More details please see Doornik(2007).
4. Q(36) is the the 36th orders of Ljung-Box Q-statistics in the levels.

Table 2: Stationary test of exchange rate volatility and stock returns

	USD/RMB	HKD/RMB	SHAI	SHBI	SZAI	SZBI	HSI
ADF	-66.905(0)	-74.047(0)	-28.802(5)	-62.148(5)	-68.201(0)	-64.365(0)	-69.892(0)
PP	-68.351(22)	-74.109(21)	-70.611(10)	-63.058(19)	-68.393(8)	-65.129(17)	69.920(12)

Notes:

1. The restrictions for the ADF and PP test at the levels of these series are a constant without trend.
2. Both the critical values for ADF and PP test are -3.43 at 1%level, and all the test results reject the null hypothesis at 1%level.
3. The number in parenthesis is lag length, which is selected by Schwarz information criteria(SIC) and Bartlett kernel bandwidth for ADF and PP test, respectively.

Table 3: Multivariate Granger Causality Test

	SHAI	SHBI	SZAI	SZBI	HSI	USD/RMB	HKD/RMB
Panel A: Test from the whole sample(1 January 1994 to 31 December 2012)							
SHAI		1558.71(0.000)	12.25(0.001)	16.79(0.000)	0.23(0.634)	0.31(0.580)	1.30(0.255)
SHBI	0.60(0.439)		3.02(0.082)	4.97(0.026)	3.86(0.049)	1.07(0.300)	0.05(0.827)
SZAI	9.14(0.003)	1737.37(0.000)		17.22(0.000)	0.00(0.945)	0.25(0.620)	0.41(0.521)
SZBI	4.08(0.433)	4329.36(0.000)	2.52(0.113)		1.63(0.201)	0.30(0.586)	0.07(0.785)
HSI	0.24(0.626)	408.44(0.000)	1.09(0.296)	11.12(0.001)		0.04(0.842)	0.55(0.459)
USD/RMB	0.49(0.485)	9.60(0.002)	0.00(0.954)	2.95(0.086)	12.32(0.000)		3.86(0.050)
HKD/RMB	0.15(0.670)	7.84(0.005)	0.01(0.929)	3.81(0.051)	1.70(0.193)	280.37(0.00)	
Panel B: Test from the subsample(1 July 1997 to 31 December 2007)							
SHAI		1213.11(0.000)	0.76(0.382)	23.84(0.000)	3.45(0.063)	1.73(0.189)	0.45(0.504)
SHBI	4.33(0.038)		1.74(0.187)	2.32(0.128)	7.20(0.007)	2.08(0.149)	0.24(0.626)
SZAI	2.13(0.144)	1128.46(0.000)		16.70(0.000)	0.08(0.774)	0.68(0.409)	0.17(0.684)
SZBI	3.94(0.047)	2925.89(0.000)	2.39(0.122)		2.42(0.120)	0.71(0.400)	0.33(0.567)
HSI	2.39(0.122)	119.79(0.000)	0.28(0.594)	0.38(0.539)		0.21(0.649)	2.79(0.095)
USD/RMB	0.03(0.866)	9.38(0.002)	0.29(0.587)	1.68(0.195)	1.87(0.172)		0.53(0.466)
HKD/RMB	0.16(0.690)	6.66(0.010)	0.18(0.668)	2.76(0.097)	0.10(0.752)	387.84(0.000)	
Panel C: Test from the subsample(1 January 2008 to 31 December 2012)							
SHAI		1213.11(0.000)	0.76(0.382)	23.84(0.000)	3.45(0.063)	1.73(0.189)	0.45(0.505)
SHBI	4.33(0.038)		1.74(0.018)	2.32(0.128)	7.20(0.007)	2.08(0.149)	0.24(0.626)
SZAI	2.13(0.144)	1128.46(0.000)		16.70(0.000)	0.08(0.774)	0.68(0.409)	0.17(0.684)
SZBI	3.94(0.047)	2925.89(0.000)	2.39(0.122)		2.42(0.120)	0.71(0.400)	0.33(0.567)
HSI	2.39(0.122)	119.79(0.000)	0.28(0.594)	0.38(0.539)		0.21(0.649)	2.79(0.095)
USD/RMB	0.03(0.866)	9.38(0.002)	0.29(0.587)	1.68(0.195)	1.87(0.172)		0.53(0.466)
HKD/RMB	0.16(0.690)	6.66(0.010)	0.18(0.668)	2.76(0.097)	0.10(0.752)	387.84(0.000)	

Notes:

1. The Granger causality test is testing the coefficient of each lagged parameter applying the Wald test.
2. The numbers in the parenthesis are P-values.

Table 4: MS models selection

Model	logL_T	AIC	SC
Panel A: Information criteria from the whole sample			
VAR unrestricted	125846.2	-51.406	-51.332
SVAR	125872	*NA*	*NA*
2 states, all-change	124054.395	-50.658	-50.599
2 states, switching coefficient	133712.513	-54.600	-54.533
2 states, switching variance	133712.513	-54.600	-54.533
3 states, all-change	124054.695	-50.58	-50.599
3 states, switching coefficient	136894.876	-55.893	-55.801
3 states, switching variance	**137273.818**	**-56.031**	**-55.883**
Panel B: Information criteria from the subperiod(01/07/1997-31/12/2007)			
2 states, all-change	71018.512	-52.438	-52.342
2 states, switching coefficient	**78247.333**	**-57.773**	**-57.662**
2 states, switching variance	78262.776	-57.769	-57.612
3 states, unrestricted	71222.758	-52.581	-52.461
3 states, switching coefficient	72283.871	-53.354	-53.204
3 states, switching variance	72283.871	-53.323	-53.081
Panel C: Information criteria from the subperiod(01/01/2008-31/12/2012)			
2 states, all-change	33632.550	-52.523	-52.346
2 states, switching coefficient	34794.682	-54.330	-54.124
2 states, switching variance	34547.171	-53.910	-53.619
3 states, all-change	33717.623	-52.639	-52.417
3 states, switching coefficient	34795.523	NA	NA
3 states, switching variance	**35066.098**	**-54.660**	**-54.213**

Notes:

1. NA indicates that the MS model can not converge based on such restrictions.
2. The information criteria have a general form$C(\theta) = -2logL_T(\theta) + C_T \times dim$
3. The bold text suggests the best MS model for each sample.

Table 5: Transition probabilities among states

MS model	Transition probabilities
Panel A: the whole sample period	
3 states,switching variance	$\begin{bmatrix} 0.8690 & 0.0768 & 0 \\ 0.1310 & 0.8463 & 0.1828 \\ 0 & 0.0768 & 0.8172 \end{bmatrix}$
Panel B: 01/07/1997-31/12/2007	
2 states, switching coefficient	$\begin{bmatrix} 0.8699 & 0.0521 \\ 0.1301 & 0.9479 \end{bmatrix}$
Panel C: 01/01/2008-31/12/2012	
3 states,switching variance	$\begin{bmatrix} 0.9115 & 0.0503 & 0 \\ 0.0885 & 0.8993 & 0.0346 \\ 0 & 0.0503 & 0.9654 \end{bmatrix}$

Figure 1: **Plots of original series**

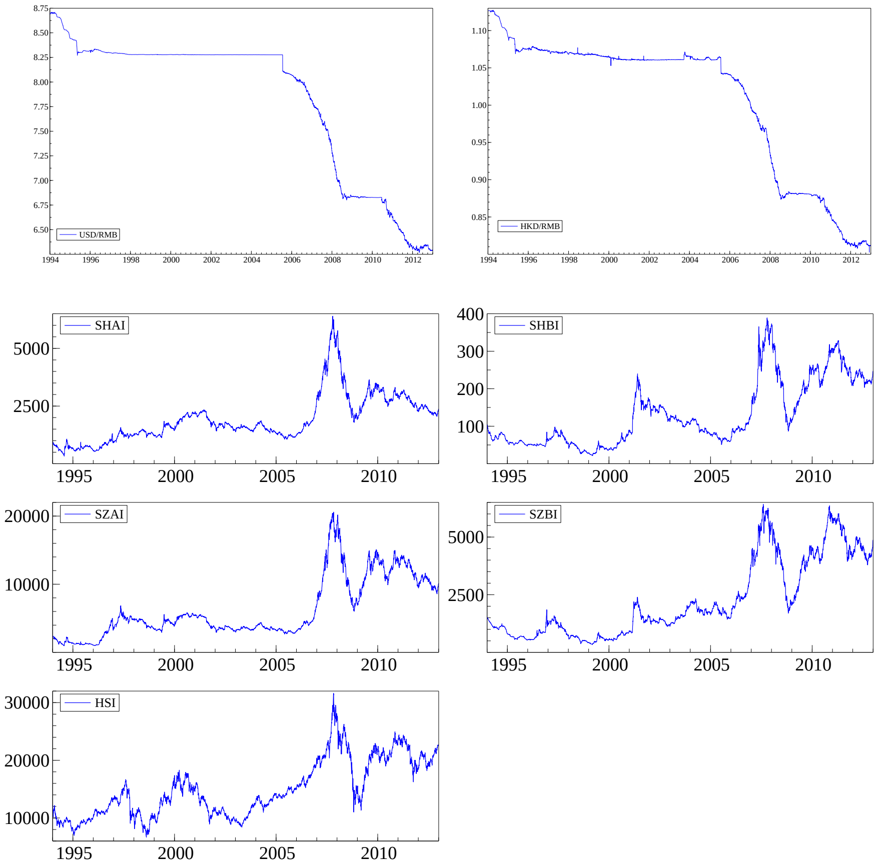

Figure 2: **Smoothed state probabilities for the whole sample**

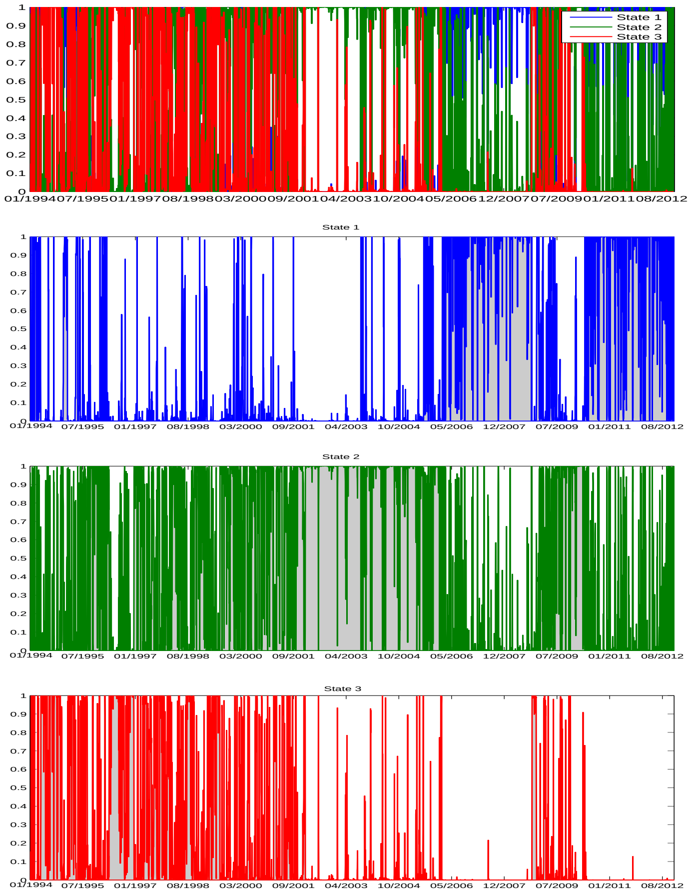

Figure 3: **Smoothed state probabilities for the subsample**

(01/07/1997-31/12/2007)

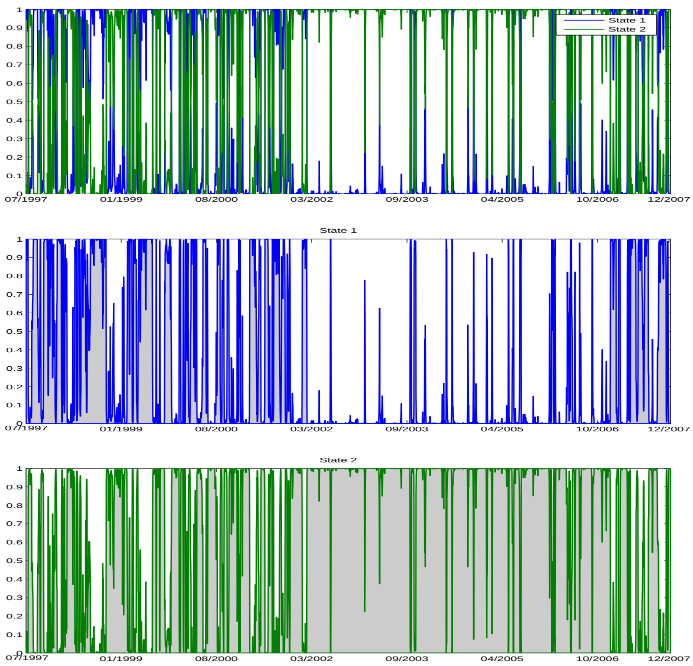

Figure 4: **Smoothed state probabilities for the subsample**

(01/01/2008-31/12/2012)

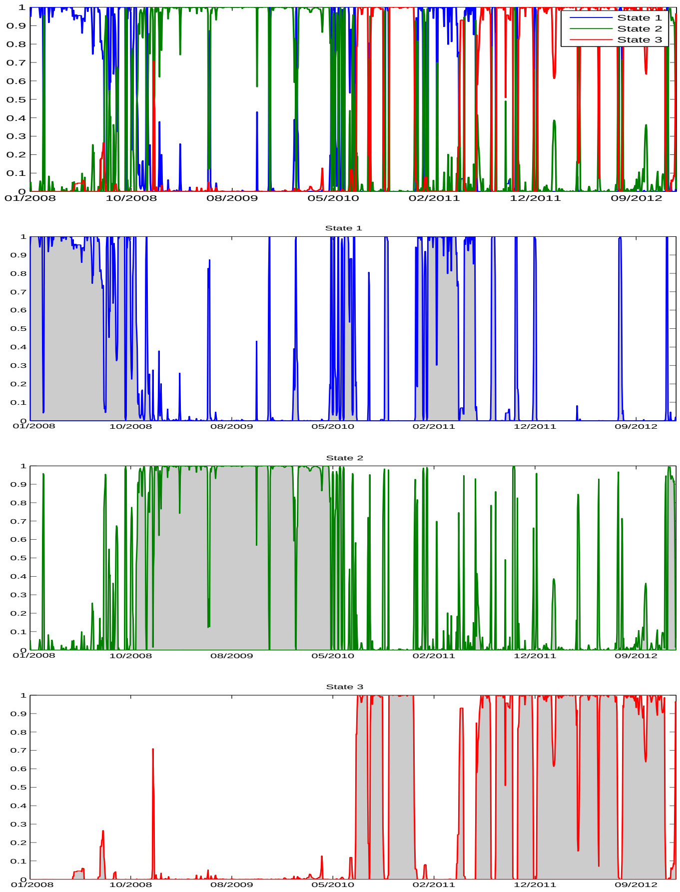

Figure 5: **Impulse responses with parameter uncertainty**

(Sample period:01/01/1994-31/12/2012)

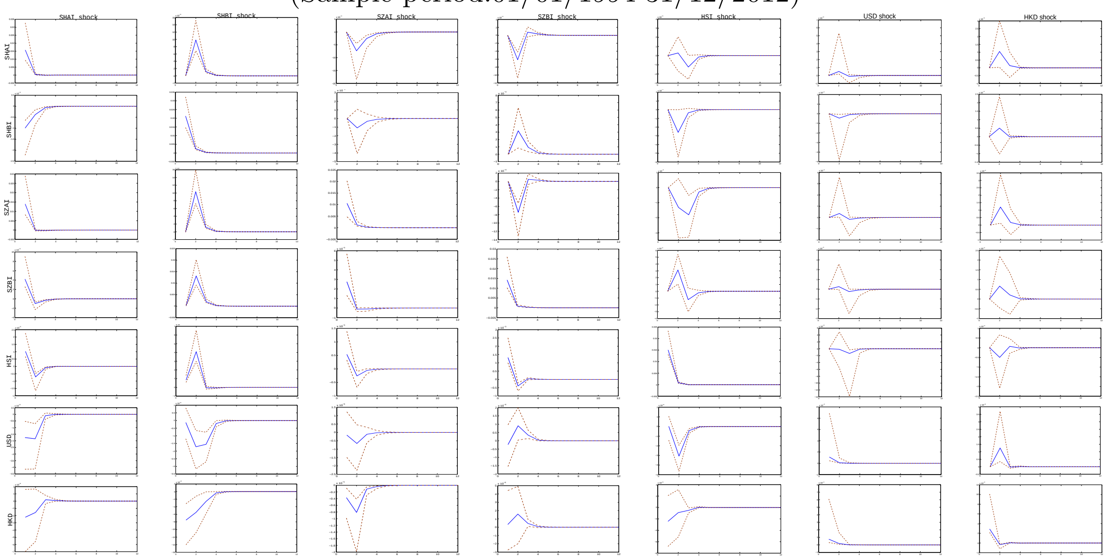

Figure 6: **Impulse responses with parameter uncertainty**

(Sample period:01/07/1997-31/12/2007)

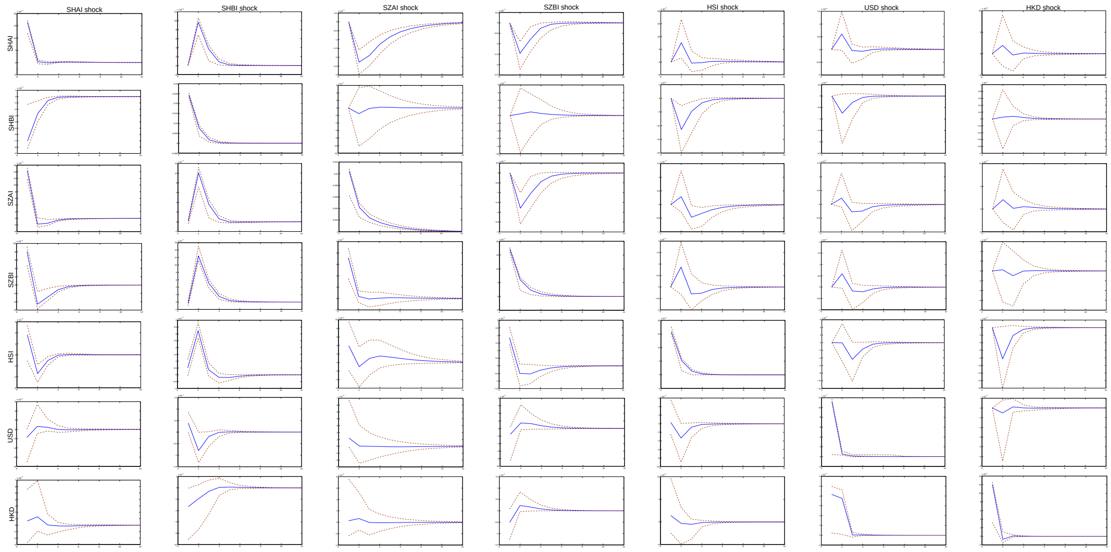

Figure 7: **Impulse responses with parameter uncertainty**

(Sample period:01/01/2008-31/12/2012)