Modeling China Stock Markets and International Linkages

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Abstract

In this paper we analyze the China stock markets and examine their price and volatility linkages with those of Hong Kong, Taiwan and United States. In particular, we analyze the direction of information flow among A-share and B-share stocks of Shanghai and Shenzhen Stock Exchanges as well as Hong Kong H-share and Red-Chip markets. We employ two methods. The first approach employs direct graph theory to determine the contemporaneous causal order of the residual vectors obtained from restricted VAR model and then use the Bernanke-Sims decomposition to compute the impulse response. The second approach involves estimating the multivariate GARCH models of several market returns to investigate the directions of spillover in mean level as well as in volatility level.

We analyze close-to-open, open-to-close, and close-to-close returns to differentiate foreign and own market effects. We also carefully model the day-of-the-week effect and the impact of the event of opening B-share market to domestic investors on February 28, 2001 to avoid misspecification of the model. Using the data from January 5, 2000 to May 30, 2003, we conclude that Chinese stock markets have a weak linkage with Hong Kong, Taiwan and US markets. As for the four domestic markets, spillover in mean returns goes unidirectionally from A-share market to B-share market but spillover in volatility is bidirectional. Further, Shanghai stock market seems to play a dominating role over Shenzhen stock market.

1 Introduction

China stock markets have attracted a lot of attention of investors and finance analysts for their fast growth and their unique feature of market segmentation. Shanghai Stock Exchange and Shenzhen Stock Exchange were established in November and December of 1990 respectively. In 2002, there are 759 stocks traded in Shanghai Stock Exchange with annual trade volume of 205.6 billion USD while 551 listed securities are traded in Shenzhen Stock Exchange with annual trade volume of 141 billion USD. Both markets have completely segmented trading between domestic investors and domestic investors. An A-share market is open only to Chinese domestic investors and a B-share market only to foreign investors. Shanghai B-share market is denominated and traded in US Dollars while Shenzhen B-share market in Hong-Kong dollars. A-share markets are traded, of course, in Renminbi (RMB), the legal currency of China.

A few stocks are listed in both markets for which Bailey(1994) notes the big price discounts of B-share relative to A-share. However, the gap has significantly shrunk since the February 28, 2001. At this important date, the restriction was lifted and domestic investors are legally allowed to trade in both B-share markets but the trade currencies remain to be US Dollars and Hong Kong Dollars respectively. A-share markets remain only open to domestic investors. As of 2002, there are only 59 and 57 B-shares stocks out of 759 and 551 stocks traded in Shanghai and Shenzhen markets respectively. Trade volume of B-share stocks account only about 3% of total trade volume in both markets.

Beyond explaining the price discount of B-share stocks, information asymmetry pattern among segmented markets is an important issue. It is typically assumed that domestic investors are better informed than foreign investors about the value of local assets. However, some researchers argue that foreign investors can be better informed than domestic investors for advanced ability to analyze information and more stringent requirement for corporate information disclosure in B-share market. What is more important, A-share markets are filled with individual investors while B-share market are mostly institutional investors. Previous researches find mixed results for information asymmetry. Chui and Kwok (1998) and Mok and Hui (1998) find B-share investors to be better informed while Chakravarty, Sarkar and Wu (1998) and Su and Fleisher (1999) support the other direction. Chen, Lee and Rui (2001) argues no information asymmetry.

This paper addresses the following questions. First, how strong are the linkages of China stock markets with those in Hong Kong, Taiwan and US? Secondly, within the four China domestic markets, what are the causal chain between A-share and B-share markets as well as Shanghai and Shenzhen stock markets? To answer these questions, we employ two methods. For the first approach, we carefully build a VAR models for the returns under investigation. We emphasize that instead of estimating the unrestricted VAR, we should remove the insignificant parameters and estimate the restricted model. The reduction of number of parameters and improvement of estimation precision are substantial. Then, we employ direct graphs theory to determine the contemporaneous causal order of the residual vectors obtained from restricted VAR model. See Pearl (1995), Spirtes, Glymour, and Scheines for details on graphs analysis. The causal ordering is transformed into restrictions in the Bernanke-Sims decomposition and the impulse response is computed to study the spillover across markets. The second approach involves estimating the multivariate GARCH models of several market returns to investigate the directions of spillover in mean level as well as in volatility level. To double check our empirical results, we examine simple cross correlations among stock returns of China stock markets, Hong Kong, Taiwan, and US markets.

The empirical results support the hypothesis of information advantage of domestic investors in A-share market over B-share markets. Also, we found no linkages of China stock markets with Hong Kong, Taiwan, and US stock markets.

By this empirical application, this paper attempts to bring together restricted VAR modeling, direct graph theory, Bernanke-Sims decomposition and impulse response analysis. Though we are not the first one to combine direct graph method with VAR modeling (Yang (2003), Bessler and Yang (2003), and Reale and Wilson (2000)), we strongly believe that the proposed procedure could become a powerful tool in analyzing dynamic relationship among variables.

In addition to this introduction, Section 2 discusses the econometric methods and data are described in Section 3. Section 4 summarizes empirical findings and conclusions are put in Section 5.

2 Econometric Methods

In this section, we shall discuss the details of building restricted VAR models, direct graph theory and multivariate GARCH models.

2.1 Estimating restricted VAR models

We select lag, p, of VAR model by examining the AIC, partial autocorrelation coefficient matrix and their associated chi-square test statistics. The essential criterion is to choose the model with minimal p such that there are no remaining autocorrelation among residuals and coefficient matrix for lag p are significantly different from zero. See Tiao and Box (1981) and Tiao (2001) for details.

Next, the VAR(p) model is estimated using exact maximum likelihood estimate method with the parameter estimates of conditional maximum likelihood estimates as initial values. Typically, a lot of parameters are insignificant. As insignificancy might arise due to multi-collinearity among variables, removing all insignificant parameters simultaneously might cause the residuals to deviate from white noise vector and induce more insignificant parameters. Lin(2003) proposes to first remove all parameters with t-value less than 1 and then remove the insignificant parameter with smallest t-value sequently. Finally, re-estimate the restricted model with exact MLE and apply a Wald-test for the imposed zero restrictions. Of course, one has to examine the residuals to make sure that they behave like vector white noise.

2.2 Impulse response and causal ordering

It is well known that residuals from a VAR model are generally correlated and applying the Choleski decomposition is equivalent to assuming recursive causal ordering from the top variable to the bottom variable. Changing the order of the variables will change the result of impulse response analysis. Bernanke (1986) provided a framework allowing for nonrecursive contemporary causal structure. More specifically, let u_t be the vector residuals from VAR models with mean 0 and covariance Σ. Bernanke decomposition writes u_t as $Au_t = v_t$ where A is a square matrix with conforming dimension and V_t is a vector of orthogonal shocks with diagonal covariance matrix. In other words, Σ is factored into $A^{-1} * D * A^{-1'}$ where D is diagonal with the variances of V. A has unit diagonals, but allows for the researchers to force certain $A(i,j) = 0, i \neq j$. These restrictions can be tested. Choleski decomposition restricts A to be lower triangular matrix.

Drawing on work in the area of causal modeling by Glymour and Spirtes (1988) and Spirtes, Glymour and Scheines (1993), Swanson and Granger (1997) proposes a two-step search procedure to determine A. The procedure uses economic information and examines first order partial correlations of VAR residuals in the first step and then test the implying restrictions in the second step. In this study, we rely on direct graphs theory to draw inference on causal ordering as the latter involves less subjective insights and use partial correlations up to $N-2$ where N is the number of returns under investigation. Further, priori knowledge about partial causal ordering of variables can be easily incorporated in the direct graphs analysis, which we shall turn to in next section.

2.3 Directed graphs theory

A direct graph assigns contemporaneous causal flow among a set of variables based on correlations and partial correlations. To illustrate the main idea, let X, Y, Z be three variables under investigation. $Y \leftarrow X \rightarrow Z$ represents the fact that X is the common cause of Y and Z. Unconditional correlation between Y and Z is nonzero but conditional correlation between Y and Z given X is zero. On the other hand, $Y \rightarrow X \leftarrow Z$ says both Y and Z causes X. Thus, unconditional correlation between Y and Z is zero but conditional correlation between Y and Z given X is nonzero. Similarly, $Y \rightarrow X \rightarrow Z$ states the fact that Y causes X and X cause Z. Again, conditional on

X, Y is uncorrelated with Z. The direction of arrow is then transformed into the zero constraints of $A(i,j), i \neq j$. Let $u_t = (X_t, Y_t, Z_t)'$ and then the corresponding A matrix for three cases discussed above denoted as A_1, A_2 and A_3 are:

$$A_1 = \begin{bmatrix} 1 & 0 & 0 \\ a_{21} & 1 & 0 \\ a_{31} & 0 & 1 \end{bmatrix}; A_2 = \begin{bmatrix} 1 & a_{12} & a_{13} \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}; A_3 = \begin{bmatrix} 1 & a_{12} & 0 \\ 0 & 1 & 0 \\ a_{31} & 0 & 1 \end{bmatrix}$$

The edge relation of each pair of variables characterizes the causal relation between them. No edge indicates (conditional) independence between two variables whereas an undirected edge ($X - Y$) signifies a correlation with no particular causal interpretation. A directed edge ($Y \rightarrow X$) means Y causes X but X does not cause Y conditional on other variables. A bidirected edge ($X \leftrightarrow Y$) indicates bidirection causal between these two variables. In other words, there are contemporaneous feedback between X and Y.

Several search algorithms are available and PC algorithm seems to be the most popular one. See Pearl (2000), and Spirtes, Glymour and Scheines (1993) for details. In this paper, we adopt PC algorithm and outline the main algorithm as below. First, start with a graph in which each variable is connected by an edge with every other variables. Compute the unconditional correlation between every pair of variables and remove the edge for the insignificant pairs. Compute the 1-th order conditional correlation between every pair of variables and eliminate the edge between insignificant ones. Repeat the procedure for computing i-th order conditional correlation until $i = N - 2$, where N is the number of variables under investigation. Fisher's z statistics is used in the significance test:

$$z(i,j|K) = 1/2(n - |K| - 3)^{(1/2)} ln\{\frac{(|1 + r[i,j|K]|)}{|1 - r[i,j|K]|}\}$$

where $r([i,j|K])$ denotes conditional correlation between variables, i and j conditional upon K variables, and $|K|$ number of series for K.

Under some regularity conditions, z approximates standard normal distribution. Next, for each pair of variables (Y, Z) that are unconnected by a direct edge but connected through an undirected edge through a third variable X. Assign $Y \rightarrow X \leftarrow Z$ if and only if conditional correlation of Y and Z conditioning on all possible variables combinations with the presence of X variable are nonzero. Repeat the process above until all possible cases are exhausted. If $X \rightarrow Z$, $Z - Y$ and X and Y are not directly connected, the assign $Z \rightarrow Y$. If there is a directed path between X and Y (say $X \rightarrow Z \rightarrow Y$) and there is an undirected edge between X and Y, then assign $X \rightarrow Y$.

Pearl(2000) and Spirtes, Glymour, and Scheines (1993) provide detailed account of this approach. Demiralp and Hoover (2003) present simulation results to show how the efficacy of PC algorithm varies with signal strength. In general, they find direct graphs method to be an useful tool in structural causal analysis.

2.4 Multivariate GARCH models

The mean and variance equations in a system are:

$$\begin{aligned} y_t &= B + D * dummy_t + Py_{t-1} + \epsilon_t && (1) \\ H_t &= E(\epsilon_t' \epsilon_t | I_{t-1}) && (2) \\ H_t &= C + B' \epsilon_{t-1}' \epsilon_{t-1} B + A' H_{t-1} A && (3) \end{aligned}$$

where I_{t-1} contains information up to $t-1$, and $dummy_t$ measures Monday dummy . This is the M-GARCH(1,1) model. Previous research has shown that this model could capture the fundamental features of the financial markets. While higher order is feasible, the increase in number parameters often create problem for convergence in estimation. See Chou, Lin, and Wu (1999) for an example.

Denoting n as the number of endogenous variables, which is 2 in our case, Ω, A and B are symmetric nxn parameter matrices while A is a general nxn parameter matrices. This is the BEKK model of Engle and Kroner (1995). The BEKK has the advantage of being parsimonious in parameters which is due to the restrictions imposed on across and within equations. Also, it guarantee the positive definiteness of the covariance matrix.

For a nonsignificant matrix Γ the residuals from the structural equations and from the reduced form have the same GARCH structures. The likelihood function can be written as:

$$\begin{aligned} L &= \sum_{t=1}^{T} L_t && (4) \\ L_t &= \frac{n}{2} ln(2\pi) - ln|\Gamma| - \frac{1}{2} ln|H_t| - \frac{1}{2} \epsilon_t' H_t^{-1} \epsilon_t && (5) \end{aligned}$$

The maximum likelihood estimate is then applied to obtain the estimate of unknown parameters that uses the updating algorithm:

$$\theta_{i+1} = \theta_i + \rho \frac{\partial^2 L}{\partial\theta\partial\theta'} \frac{\partial L}{\partial\theta}$$

where θ contains all the parameters and ρ is a scalar step length. Simplex algorithm is first used to obtain initial estimates and BFGS (Broyden, Fletcher, Goldfarb, and Shanno) scent methods follows as updating algorithm.

Bai, Russell and Tiao (2003) constructs analytical representations for the precision of variance estimates in the presence of volatility clustering, leptokurtosis, deterministic patterns in the volatility structure and serial correlation of the returns. However, it is unclear how the presence of ARCH error will affect the finite sample efficiency of the estimate of conditional correlation and direct graphs analysis.

3 Data and Preliminary Analysis

The data used consists of daily stock returns of Shanghai A-share (SA), Shanghai B-share (SB), Shenzhen A-share (ZA), Shenzhen B-share (ZB), Hong Kong H-share (HH), Hong Kong Red Chip (HR), Hong Kong Hang Seng Index (HS), Taiwan Stock Exchange Weighted Index (TAIEX), SP500, NASDAQ and Dow Jones indexes. HH and HR are all China based companies with HH registering in China and HR in Hong Kong respectively. Cross listing of the same company in two markets is not allowed.

We distinguish three returns: Close at time t-1 to Open at time t (CTO), Open at time t to close at time t (OTC), and Close at time t-1 (CTC) to close to time t. To be precise, three returns are defined as:

$$\begin{aligned} CTO_t &= (O_t - C_{t-1})/C_{t-1} * 100 \\ OTC_t &= (C_t - O_t)/O_t * 100 \\ CTC_t &= (C_t - C_{t-1})/C_{t-1} * 100 \end{aligned}$$

In Taiwan stock market, there is a price limit for each stock. Price of each stock is only allowed to fluctuate within the band of 7% with closing price of previous trading day. See Cho, Russell, Tiao and Tsay (2002) for an analysis of the effect of these price limits.

All data are taken from database of Taiwan Economic Journal ranging from January 5, 2000 to May 30, 2003 with 794 observations. When US stock markets are included, number of observations reduces to 731.

The close prices of all 11 markets mentioned above are put in Figure 1. From the figure, we make the following observations. First, judging from the co-movement, we can divide 11 close prices into three groups. Group 1 consists of Dow Jones Index, NASDAQ, SP500, TAIEX, HS, and HR. SA and ZA make up the second group while the third group includes SB, ZB, and HH. Second, While group A exhibits a long-term declining trend, the second and the third groups actually display a growing trend prior to May 30, 2001. This might be explained by the fact that on February 28, 2001 the restriction of B-share to foreign traders is lifted in both Shanghai and Shenzhen markets that significantly shrank the discount of B-share market to A-share market. Two B-share markets had been shutdown for one week prior to February 28, 2001. When the B-share market is re-opened, daily return jumped up by over 9.7% for 5 (4) consecutive days in Shenzhen

(Shanghai) market. These are essentially level shifts for the daily close price for SB, ZB and HH. Third, the declining speed for China stock markets after May 30, 20001 are slightly slower that of US, Taiwan and Hong Kong market.

The descriptive statistics for 11 daily CTC returns as well as CTO and OTC returns for China stock markets are put in Table 1. The fifth column of the table is excess kurtosis. From the table, we observe the following. First, SB and ZB have the highest CTC returns followed by HH. This is due to the effect of the event of opening B-share markets to domestic investors on February 28, 2001. In our analysis, we subtract the CTC return during the period between February 28, 2001 to May 31, 2001 from the mean of this subperiod and keep observations in other subperiod unchanged. We have also tried to control the impact by adding dummy and found the results similar. Second, except for HR, all China stock returns are positive while other returns are negative during the same sample period. Third, as is obvious from the second and third panels of the table, CTO is much higher than OTC for China stock market, indicating the pattern of opening high and staying high until closing. Fourth, from the standard deviation and kurtosis, we find that A-share markets are much more volatile than B-share markets which latter are more volatile than US, Hong Kong and Taiwan stock markets. The kurtosis for the CTO of four China markets are all higher than 50 with both ZA and SA greater than 100. Fitting GARCH models or any other time series models for such high kurtosis seems impossible.

4 Empirical results

In additional to the impulse response analysis and multivariate GARCH models, we also perform simple cross correlation analysis as a preliminary analysis of the spillover effect between China stock markets, Hong Kong, Taiwan and US markets. We shall discuss the empirical results in the sequel.

4.1 Empirical results of cross correlation analysis

The cross correlation of the returns of Hong Kong, China and Taiwan stock markets with those of SP500, Dow Jones and NASDAQ are reported in Table 2. To account for different time zone, returns at time $t-1$ in US markets are paired with returns at time t for three Asian stock markets. To explore possible lead-lag relationship, we compute cross correlation for lag $l = -1, 0, 1$, where $r_{xy}(l) = Corr(x_t, y_{t+l})$. As is clear from the table, HS has the strongest correlation with US market with correlation coefficients all higher than 0.4. The correlations of HR and HH with US markets are also high with correlation coefficient higher than 0.3 for the former and around 0.2 for the latter. The correlation coefficients for Taiwan are all higher than 0.25. As for China stock markets, the correlation coefficients are all less than 0.1. We further compute the correlation of stock markets of China with Hong Kong and Taiwan and summarize the results in Table 3. From the tables we find that the correlations between stock markets of China an Taiwan are low with correlation coefficients all less than 0.08. As for the correlation between Hong Kong and China stock markets, the linkage between B-share and HS are stronger than that between A-share and HS.

To explore the possibility that spillover effects only occur when the market opens, we further compute the correlation between CTO of China stock market with US and Hong Kong markets. The results are reported in Table 4. Again, all correlations coefficients are very small with almost all less than 0.05.

Lastly, we examine the cross correlation among four China stock markets and report the results in Table 5. From the table, we find strongest linkages among two A-share markets, ZA, and SA, followed by two B-share markets, ZB and SB. Correlation between SA and SB, ZA and ZB, SA and ZB, as well as ZA and SB are about the same with value around 0.63. As for the cross-correlation between CTO and OTC as reported in the bottom panel of Table 5, we find that within the same market, the linkage is weak. In other words, opening price today is not influential of closing price today. On the contrary, OCT at t-1 has an impact of CTO at time t and the effect is across markets.

In summary, the linkage between China stock market with US, Taiwan and Hong Kong (HS) stock markets are very weak. Due to relatively small sample size, we can not include too many variables in VAR and GARCH models. Also drawing inference from the results of cross correlation analysis, we focus on 6 China stock returns (CTC), SA, SB, ZA, ZB, HR and HH in the sequel. This assumption is confirmed by applying direct graphs methods to the contemporaneous correlation matrix among these six indexes, three US stock indexes, TAIEX and HS. There are no edge linking US, Taiwan and HS with these 6 returns.

4.2 Empirical results of impulse response analysis

It is somewhat surprising the it takes lag 6 to whiten the residual. For the unrestricted mode, there are 222 parameters to estimate. We follow the proposed procedure above and obtain a restricted model with only 37 parameters. In other words, 185 parameters are restricted to be zero and their associated variables are removed from the model. The significance pattern of the estimates are reported in Table 6, where '.' means insignificant, '+' positively significant and '-' negatively significant. The χ^2 test statistics is 209.0327 which gives p-value 0.1087. Thus, we cannot reject the null hypothesis that 185 parameters are equal to zero. We further examine the diagnostic checking statistics of residual vector and do not find remaining autocorrelation.

Next, we apply the direct graphs theory to the covariance matrix of the restricted model and obtain the causal graphs as in 2. The graph read as below. (1) HH and HR are independent of ZA, ZB, SA and SB. (2) HH and HR are related but graphs theory is inclusive about causal order. (3). ZA and SB causes ZB. ZA and ZB are related but causal direction is inconclusive. Similarly for SA and SB. Drawing upon the findings of correlation analysis, we assign the causal order for the three inconclusive cases as $SA \rightarrow ZA, SA \rightarrow ZB$ and $HR \rightarrow HH$. The pattern matrix in the Bernanke-Sims decomposition for corresponding A matrix used in impulse response analysis become

$$A^0 = \begin{bmatrix} 1 & 0 & 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 & 1 \end{bmatrix}$$

The impulse response of the effects of one market to other markets are put in Figures 3 to 8. From these graphs, we make the following observations. First, information flow goes from A-share market to B-share market and not the other way around. In other words, shocks to A-share market transmit to B-share market but shocks to B-share market have no significant effect on A-share market. Second, the speed of spillover in Shanghai market is faster than that of Shenzhen market. Shocks in Shanghai A-share market affect instantaneously Shanghai B-share market and Shenzhen B-share market while shocks in Shenzhen A-share market does not have impact on Shanghai B-share market until 6 days later. Third, shocks in Shanghai A-share market have an instantaneous impact on Shenzhen A-share market but it takes 4 days for the impact from the opposition to be effective. This result is no surprising as B-share markets only account for 3% of total stock transaction and volume of transaction in Shanghai market is larger than that of Shenzhen market. In addition, Shanghai has been viewed as the financial center of China and receive more attention than Shenzhen market. Fourth, ZB stays in the bottom of the causal chain by receiving impact from ZA, SA, and SB but does not affect other markets. Fifth, HH behaves like ZB to reflect impact on ZA, SA, SB and HR. Sixth, HH and HR do not have significant effect on China domestic stock markets.

4.3 Empirical results of GARCH modeling

The estimation results of M-GARCH model are reported in Table 7. As is obvious from the table, the multivariate GARCH model basically confirm the findings of previous two methods. The findings for the mean of the returns are: (1) spillover run unidirectionally from A-share market to B-share market within each market and across markets; (2)there exist feedback between SA and

ZA. Similarly, feedback are found for SB and ZB. As for volatility level, each market is affected by other markets. In other words, volatility spillover from any market to other markets.

We shall conclude this section by comparing our findings with those of Yang(2003). Yang (2003) builds an unrestricted VAR(1) for same six returns as ours for the data from January 2, 1995 to December 29, 2000. He also applies direct graphs theory to determine the contemporaneous causal order followed by a forecast error decomposition. He started with level VAR, test for cointegration, convert the cointegrated model back to level VAR and then perform forecast error decomposition. We analyze three different returns and do not need to worry about cointegration. We choose to perform response analysis and report confidence interval by simulation. We use most recent data from January 5, 2001 to May 30, 2003. Yang concludes causal order from ZB to ZA and SA to SB while we find causal flow from A-share to B-share. The difference might arise from different sample periods but considering the size of B-share markets to A-share markets, we believe that our findings are more reasonable.

5 Conclusions

We have combined directed graphs theory with impulse response to study the linkage of China stock markets with US, Hong Kong and Taiwan stock markets. We also employ multivariate GARCH models to analyze the mean and volatility spillover among China stock market. The empirical analysis find weak linkage between China stock market with US and Taiwan stock markets. It seems that China stock markets do not synchronize with these stock markets. As for the four domestic markets, spillover in mean returns goes unidirectionally from A-share market to B-share market but spillover in volatility is bidirectional. Further, Shanghai stock market seems to play a dominating role over Shenzhen stock market.

Table 1: Descriptive Statistics for 11 stock returns

Stock	Mean	SD	Skewness	Kurtosis
Close-to-Close return				
DJ	-0.00612	1.41092	0.22089	1.45811
NASDAQ	-0.05763	2.60803	0.45478	1.80180
SP500	-0.02632	1.47399	0.27820	1.06206
TX	-0.02466	1.89690	0.23023	0.60562
HS	-0.04417	1.59629	-0.06570	1.82112
HR	-0.01955	2.29318	0.25197	2.87506
HH	0.11891	2.06231	0.58156	3.06123
SA	0.06253	1.42137	1.13759	9.23670
SB	0.23601	2.42950	0.65727	3.67997
ZA	0.05802	1.48472	0.89229	7.87250
ZB	0.22115	2.51285	0.75152	3.84218
Close-to-Open return				
SA	0.06550	0.62910	8.86420	109.27130
SB	0.13004	1.02210	6.35959	53.12769
ZA	0.04632	0.60453	8.95247	110.01810
ZB	0.16490	0.92401	7.63606	70.44921
Open-to-Close return				
SA	-0.00277	1.28681	0.12750	3.82135
SB	0.01908	2.14690	0.16884	4.08185
ZA	0.01184	1.36452	0.10340	3.85243
ZB	0.05838	2.42293	0.25318	3.93920

Table 2: Cross-Correlation of HongKong, Taiwan and China Stock Markets with US Stock Market

Stock		DJ	NASDAQ	SP500
Hong Kong Stock Market				
HS	-1	0.0544	0.0235	0.0547
	0	0.4216	0.463	0.4651
	1	0.0946	0.1233	0.1092
HR	-1	0.0094	0.0051	0.0117
	0	0.3042	0.3325	0.3385
	1	0.1283	0.1118	0.1257
HH	-1	-0.035	-0.0713	-0.0447
	0	0.1865	0.2031	0.2082
	1	0.0547	0.0802	0.0631
Taiwan Stock Market				
TX	-1	0.0205	0.1026	0.0453
	0	0.2513	0.2595	0.2672
	1	0.1024	0.1295	0.1082
China Stock Market				
SA	-1	0.0065	-0.0151	0.0002
	0	0.0175	0.0186	0.0137
	1	-0.0475	-0.0449	-0.0482
SB	-1	-0.0099	-0.0721	-0.0333
	0	0.0828	0.0485	0.0698
	1	-0.021	-0.0453	-0.0343
ZA	-1	0.0128	-0.0168	0.0032
	0	0.0173	0.0234	0.0147
	1	-0.0502	-0.0479	-0.0521
ZB	-1	-0.0141	-0.058	-0.0296
	0	0.0936	0.0844	0.092
	1	-0.024	-0.0249	-0.0279

Table 3: Cross-Correlation of China Stock Markets with Taiwan and Hong Kong Stock Markets

Stock		TX	HS	HR	HH
SA	-1	0.0792	0.024	0.0351	-0.0132
	0	-0.0179	0.0868	0.0928	0.1249
	1	0.0012	-0.0665	-0.0299	-0.0737
SB	-1	0.0399	0.0064	0.0007	0.0054
	0	0.047	0.1342	0.1121	0.1429
	1	-0.0316	-0.0525	-0.0389	-0.0944
ZA	-1	0.0771	0.0218	0.0383	-0.0173
	0	-0.0148	0.0796	0.0824	0.1172
	1	-0.0041	-0.0653	-0.0296	-0.0804
ZB	-1	0.0715	-0.0024	-0.0113	-0.027
	0	0.0599	0.1485	0.1119	0.1152
	1	-0.0112	-0.0344	-0.0216	-0.0697

Table 4: Cross-Correlation of China, US and Hong Kong Stock Markets

Stock		DJ	NASDAQ	SP500	HS	HR	HH
		Close-to-Close					
SA(Close-to-Open)	-1	0.0161	0.0063	0.003	0.0904	0.0998	0.0522
	0	0.0092	-0.0076	-0.0024	0.0347	0.0635	0.0336
	1	0.0246	0.0453	0.0256	-0.0109	0.0183	-0.0016
SB(Close-to-Open)	-1	0.0137	-0.0132	-0.0002	0.0203	0.0301	0.0476
	0	0.0635	0.031	0.0475	0.0735	0.0968	0.0808
	1	0.021	0.0503	0.0237	0.0303	0.0494	-0.0032
ZA(Close-to-Open)	-1	0.0138	0.0078	0.0022	0.082	0.0879	0.046
	0	0.0087	-0.0107	-0.0067	0.0301	0.0607	0.0356
	1	0.0258	0.0381	0.0223	-0.0096	0.0133	-0.0036
ZB(Close-to-Open)	-1	0.0033	-0.0149	-0.0127	0.0304	0.0382	0.0364
	0	0.0564	0.0412	0.0461	0.0445	0.0709	0.0372
	1	0.0142	0.0342	0.0127	0.0168	0.0243	0.0103

Table 5: Cross-Correlation among 4 China stock markets

Close-to-Close return					
		SA	SB	ZA	ZB
SA	-1	0.0071	0.0024	0.0037	0.0029
	0		0.6293	0.9837	0.6392
	1		-0.051	0.0171	-0.0534
SB	-1		0.0711	-0.0481	0.069
	0			0.6252	0.8577
	1			0.0067	0.067
ZA	-1			0.0163	0.0086
	0				0.6397
	1				-0.05
ZB	-1				0.0987
	0				
	1				

Close-to-Open return and Open-to-Close return					
					Open-to-Close return
Close-to-Open return		SA	SB	ZA	ZB
SA	-1	0.237	0.1372	0.2505	0.1798
	0	-0.0235	-0.0176	-0.0005	-0.0005
	1	-0.0497	-0.0686	-0.0578	-0.0809
SB	-1	0.1353	0.3169	0.1523	0.3429
	0	-0.0331	0.0021	-0.0169	0.0419
	1	-0.019	-0.1739	-0.037	-0.1749
ZA	-1	0.2422	0.131	0.2598	0.1783
	0	-0.0382	-0.0231	-0.0174	-0.0131
	1	-0.0544	-0.071	-0.065	-0.0811
ZB	-1	0.1088	0.2056	0.1136	0.3082
	0	-0.0605	-0.0996	-0.0509	-0.0995
	1	0.0095	-0.082	-0.0032	-0.0665

Table 6: Significance Pattern of VAR(6) models for ZA, ZB, SA, SB, HR, and HH

C	Φ_1						Φ_2						Φ_3						Φ_4						Φ_6				
.	.	.	.	+	.	.	.	.	.	.	.	.	.	.	.	.	.	+	.	-	.	.	.	+	.	-	.	.	+
.	+	-	.	.	.	.	.	.	-	.	.	.	.	.	.	.	.	.	.	.	.	.	.	+	.	-	+	.	.
.	.	.	.	+	.	.	.	.	.	.	.	.	.	.	.	.	.	+	.	-	.	.	.	+	.	-	.	.	+
.	.	.	+	.	.	.	.	.	.	.	.	.	.	.	-	.	.	.	.	.	.	.	.	+	.	-	.	.	.
.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	-	.
+	.	.	-	.	+	.	.	.	.	.	.	-	.	+	.	.	.	.	.	.	.	.	.	.	.	.	.	.	-

The model is $y_t = c + \Phi_1 y_{t-1} + \ldots + \Phi_6 y_{t-1} + \epsilon_t$

Table 7: Estimation results of M-GARCH Models

Variable	Coeff	T-Stat	Variable	Coeff	T-Stat
B11	-0.04445112	-0.43331	VAR(1,4)	0.05615391*	9.53496
B21	0.10181669*	4.05090	VAR(2,4)	0.29447625*	3.88106
B31	-0.05478603	-1.26109	VAR(3,4)	-0.04826805*	-5.08553
B41	0.09497512*	4.03400	VAR(4,4)	0.23577822*	6.68491
P11	-0.28089090	-0.65104	VBR(1,1)	0.14171402	1.42091
P12	8.82740179	0.67691	VBR(2,1)	0.04967372	0.59293
P13	-0.15115793	-0.51755	VBR(3,1)	-0.45802221*	-4.62600
P14	0.01414863	0.39029	VBR(4,1)	0.08206867	0.97202
P21	-0.29824932*	-2.82117	VBR(1,2)	-0.00717032	-0.78140
P22	-15.38251335*	-4.69848	VBR(2,2)	0.03958990*	4.47419
P23	0.44622415*	6.23518	VBR(3,2)	-0.01028988	-1.18250
P24	-0.00369124	-0.40546	VBR(4,2)	-0.01107684	-1.25432
P31	-0.41107393*	-2.24977	VBR(1,3)	-0.14897222*	-2.27443
P32	9.70186891	1.75732	VBR(2,3)	0.06011878	1.29799
P33	-0.09785808	-0.79108	VBR(3,3)	-0.26872156*	-4.31539
P34	0.02119631	1.38132	VBR(4,3)	0.05936620	1.28909
P41	-0.09879660	-0.99764	VBR(1,4)	-0.00587779	-0.64042
P42	-15.84666602*	-5.18329	VBR(2,4)	0.00062476	0.06941
P43	0.65677240*	9.79800	VBR(3,4)	-0.01147905	-1.31997
P44	0.03834491*	4.51190	VBR(4,4)	0.02754570*	3.04940
D11	0.12393901	1.35966	VCR(1,1)	-0.27177852*	-17.53479
D21	-0.01885947	-0.59523	VCR(2,1)	-0.14299456*	-6.41426
D31	0.20534747*	2.26987	VCR(3,1)	0.99118882*	63.50114
D41	-0.01863376	-0.58740	VCR(4,1)	0.66324548*	28.09564
VAR(1,1)	0.37132528*	9.96133	VCR(1,2)	0.00000000*	0.00000
VAR(2,1)	3.40155005*	10.83752	VCR(2,2)	0.00036685	1.76877
VAR(3,1)	-0.83431218*	-16.86891	VCR(3,2)	-0.00014395	-1.15624
VAR(4,1)	-3.01468282*	-9.31696	VCR(4,2)	2.22751027*	185.30643
VAR(1,2)	0.05631398*	9.52214	VCR(1,3)	0.00000000*	0.00000
VAR(2,2)	0.22660018*	3.41087	VCR(2,3)	0.00000000*	0.00000
VAR(3,2)	-0.04823599*	-5.11427	VCR(3,3)	1.11517483*	91.33073
VAR(4,2)	0.30376753*	8.35691	VCR(4,3)	0.58193455*	23.07853
VAR(1,3)	0.28143830*	10.32185	VCR(1,4)	0.00000000*	0.00000
VAR(2,3)	0.16918025	0.84987	VCR(2,4)	0.00000000*	0.00000
VAR(3,3)	-0.82744753*	-18.70388	VCR(3,4)	0.00000000*	0.00000
VAR(4,3)	0.26008434	1.34636	VCR(4,4)	2.22780914*	186.39122

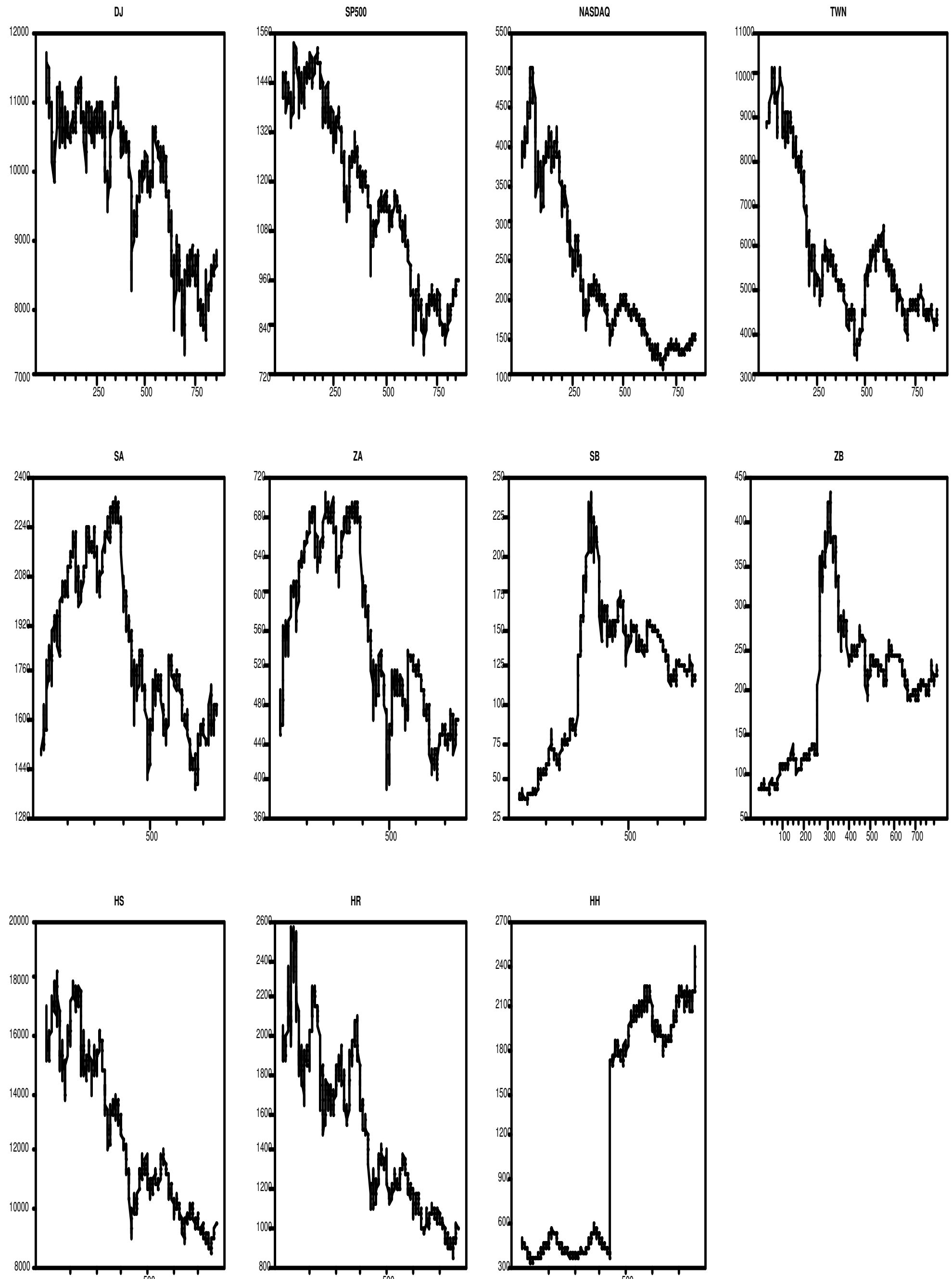

Figure 1: Time Series Plots for 11 market closing prices

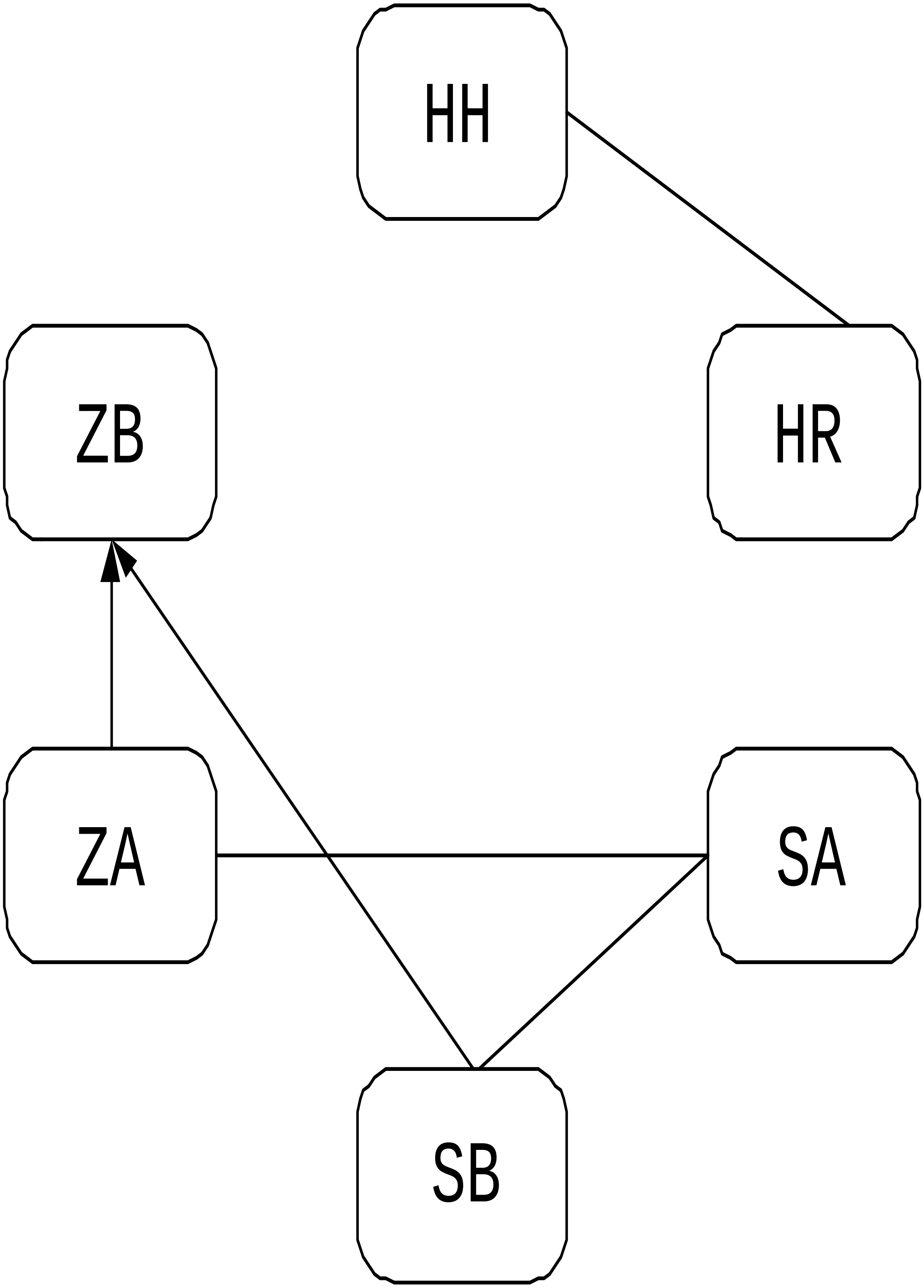

Figure 2: Causal graph of ZA, ZB, SA, SB, HR and HS

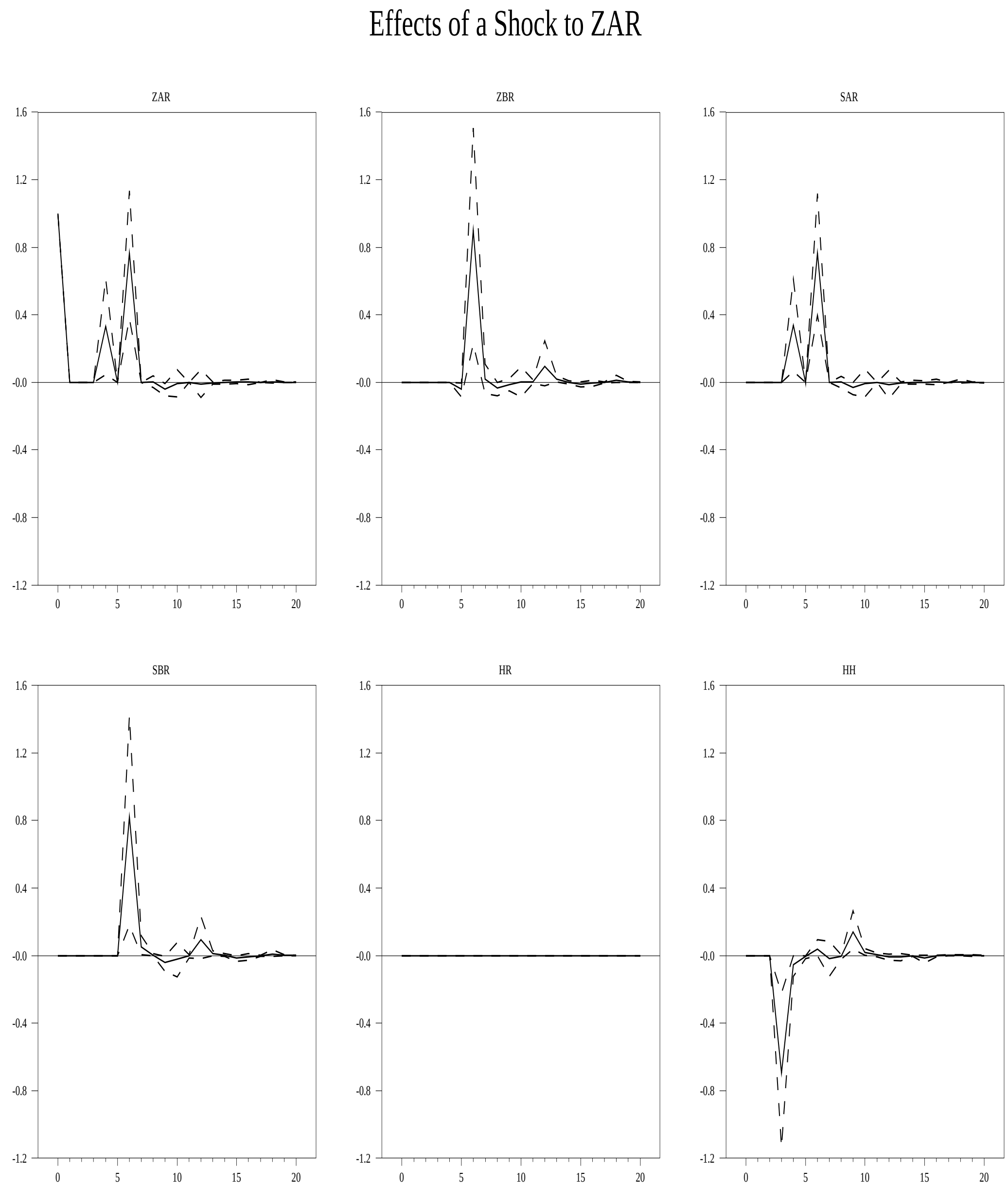

Figure 3: Impulse response of the effect of a shock to Shenzhen A-share returns

Effects of a Shock to ZBR

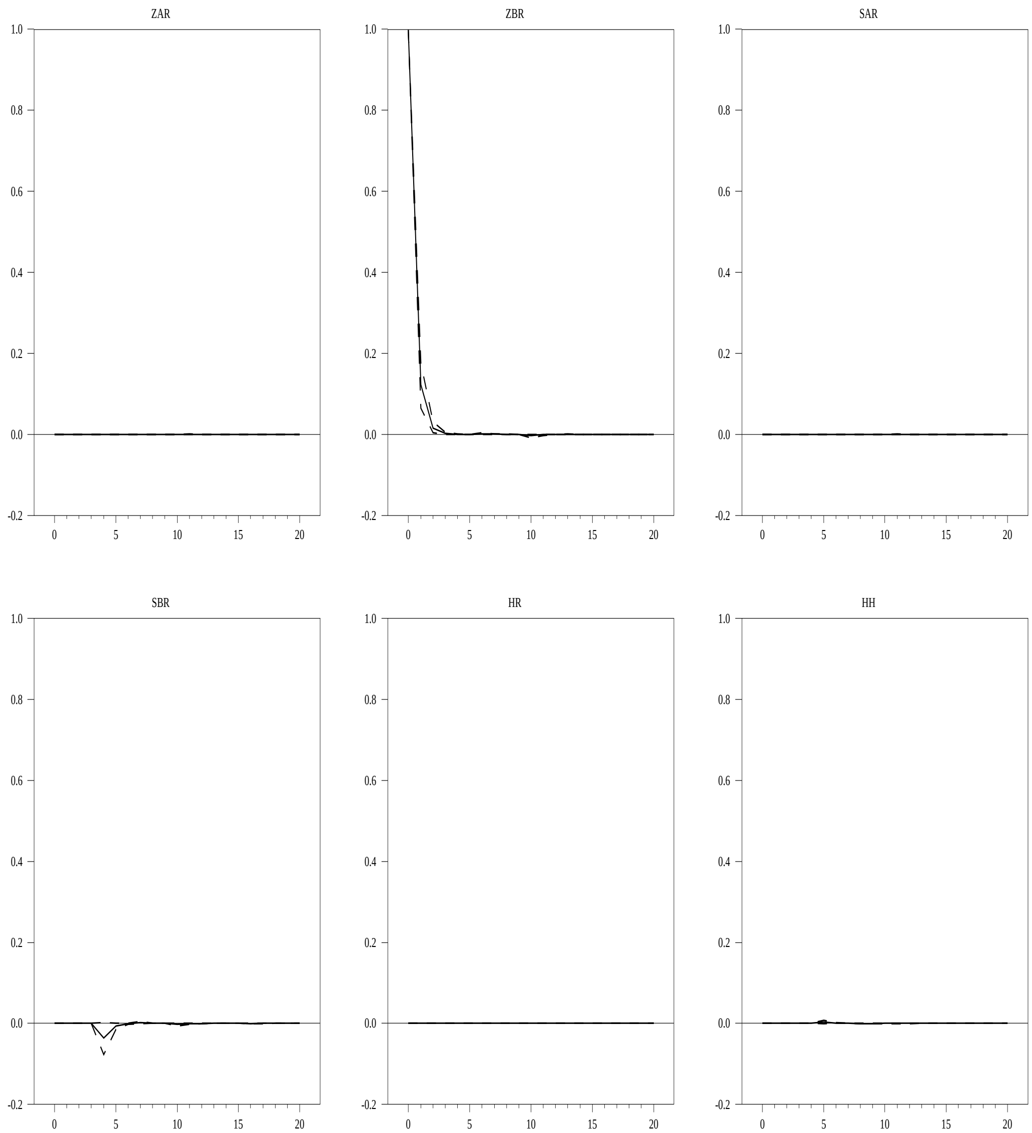

Figure 4: Impulse response of the effect of a shock to Shenzhen B-share returns

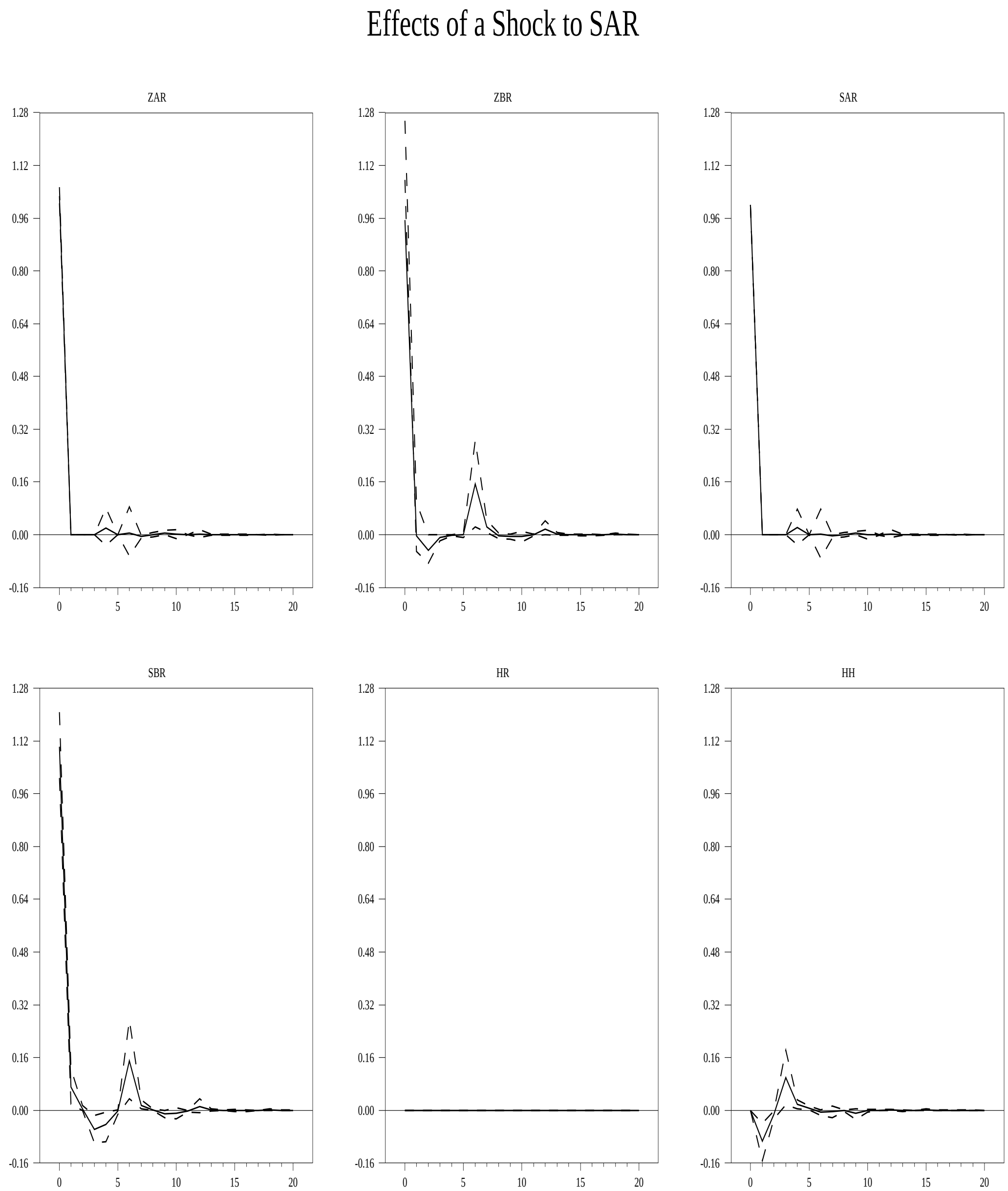

Figure 5: Impulse response of the effect of a shock to Shanghai A-share return

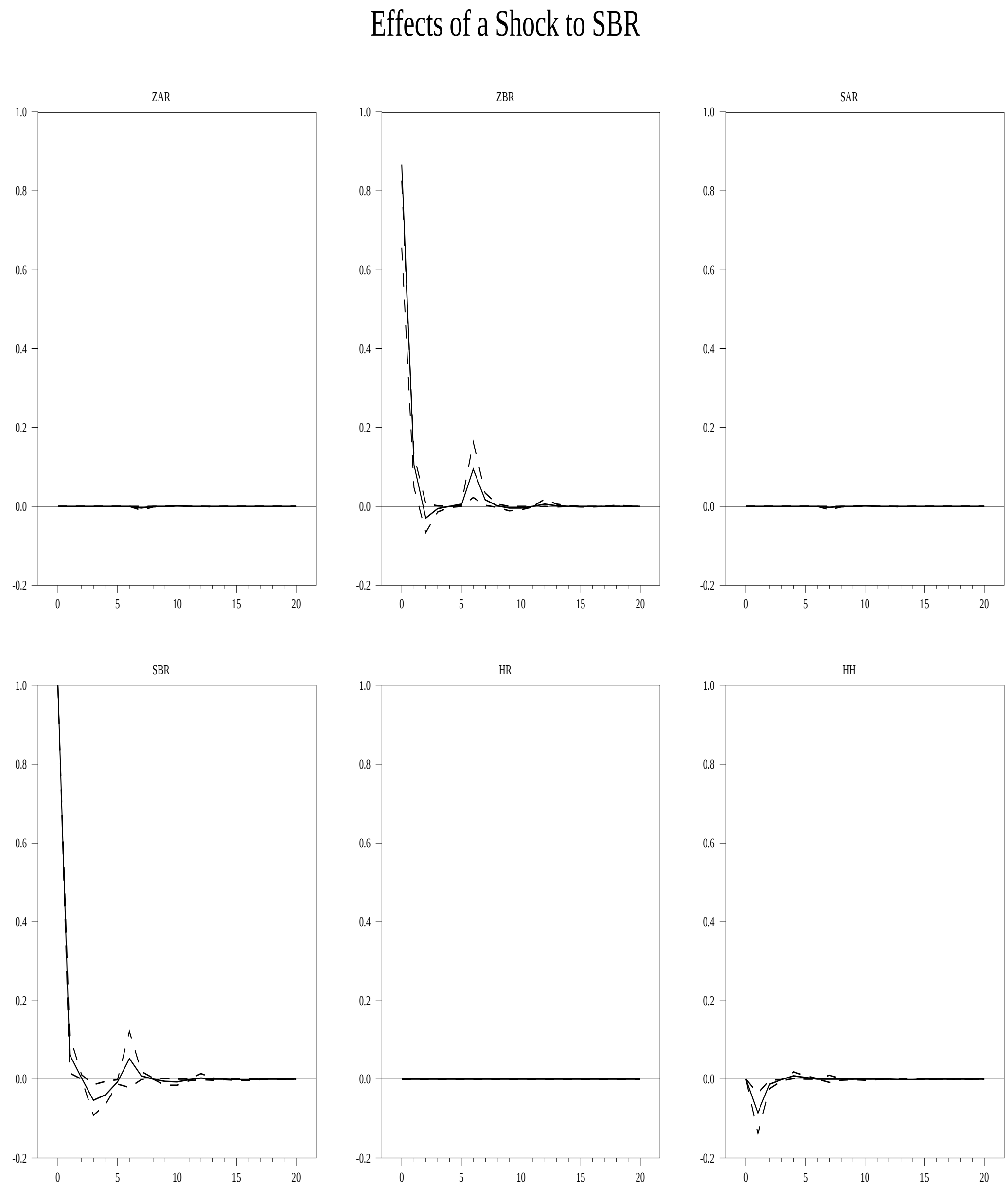

Figure 6: Impulse response of the effect of a shock to Shanghai B-share return

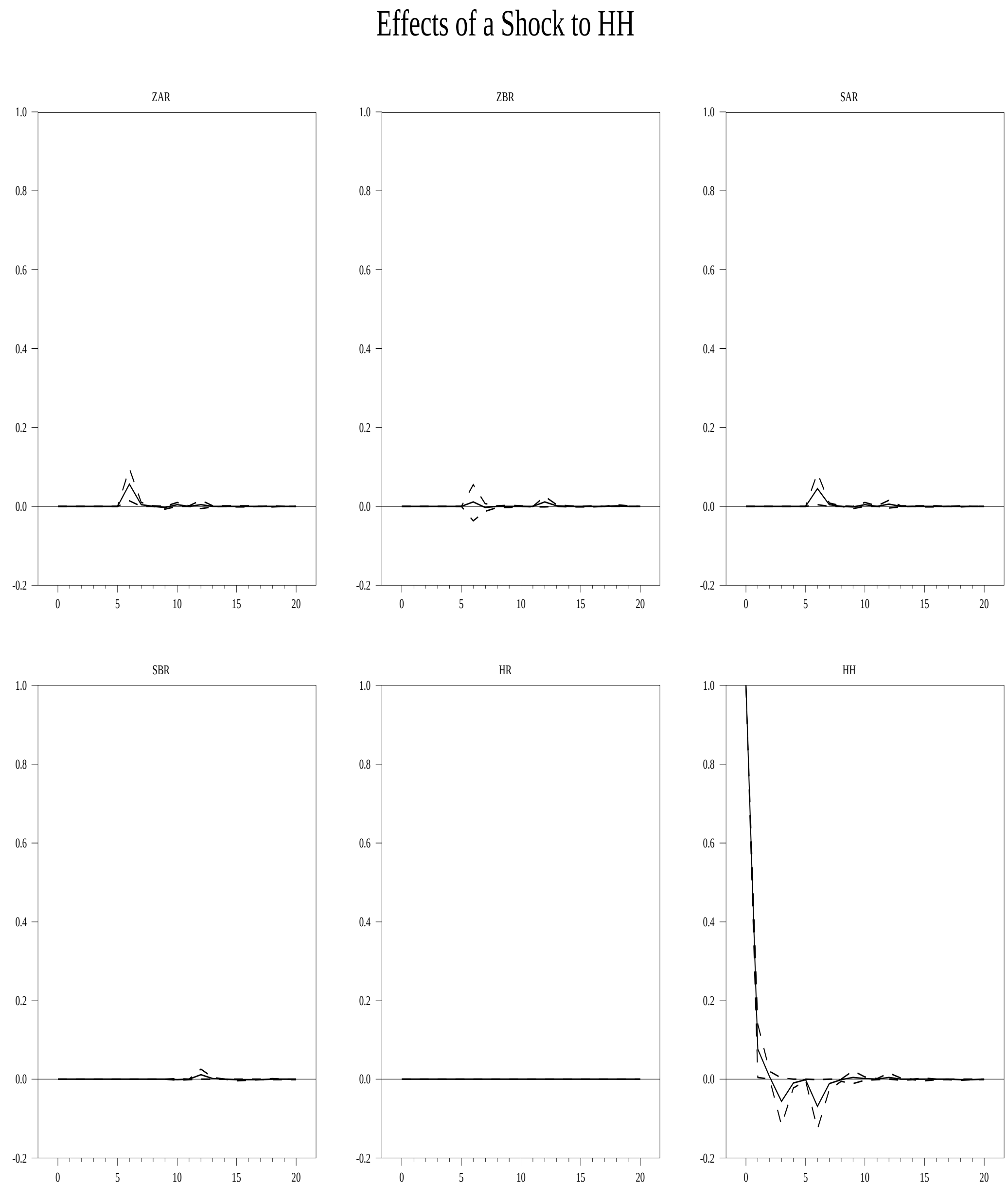

Figure 7: Impulse response of the effect of a shock to Hong Kong H-share return

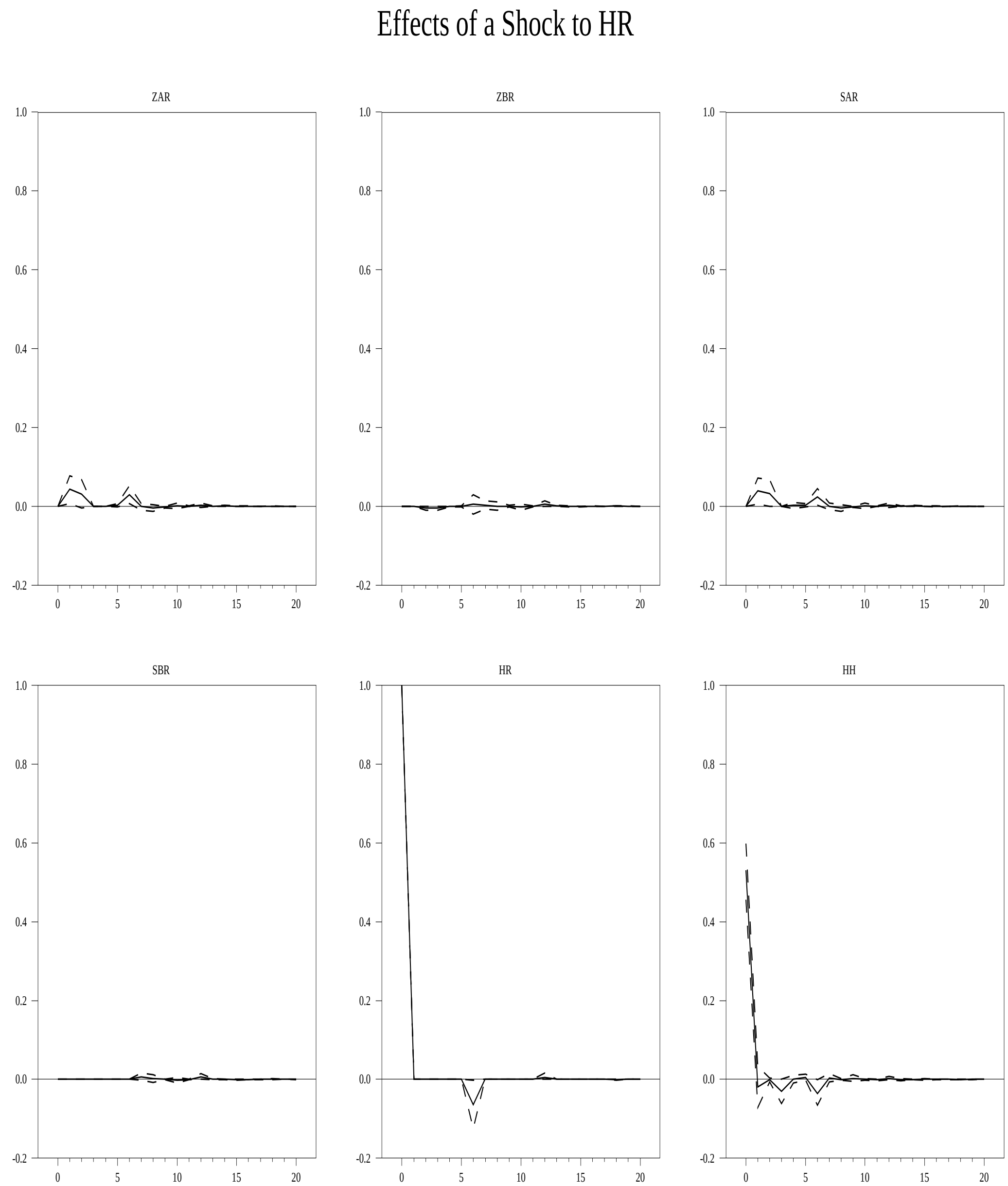

Figure 8: Impulse response of the effect of a shock to Hong Kong Red-chip return

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