Warning Signals of Stock Market Crash during Financial Crisis: Using Hong Kong as an Empirical Study

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Abstract

There is a large literature using macroeconomic variables such as exchange rate, HIBOR, money supply and T-bill rate, to estimate the likelihood of financial crisis. This paper is a case study of Hong Kong Stock Exchange. The sample period is from 1987 to 2013 to capture the three financial crises. Using Vector Autoregressive (VAR) and Vector Error Correction Models, we find that HIBOR can predict the stock market price in one or two month in advance of the financial crisis.

1. Introduction

People always talk about financial crisis, stock market crash, and economic downturn. How negative the impacts are they brought to the people? Most correlated to people, stock market crash makes the value of the stock share plummet. Many investors suffer a substantial decline in value of the stock they hold. This decline is very likely to cause negative impact son household consumption spending through the wealth effect, business investment spending, the demand for money, and other economic variables (Hsing, 2011).

Another negative impact of stock market crash during the financial crisis is the employment rate. Unemployment has speedy increase in every member countries of European Union since March 2008 after the global economic crisis. Although the severity of the extent varies widely between countries and regions, the influences to people are universal. What is more we are concerned about is the domino effect created by the stock market crash, which means one problem is often linked to another. For instance, reduced employment rate can result in decreased investment, leading to significant drop in asset value.

To reduce the probability of another financial collapse, it is necessary to learn from experience by identifying ultimate sources of the incentives that led to the crisis. It means that we should not only explain the crisis but to enable anticipation of future ones. We want to forecast stock market crash before financial crisis to decrease the loss. When selecting the method, we decided to use Granger causality test and Vector Autoregressive model (VAR) to test the time lag. Dhakal, Kandil, and Sharma (1993) used a vector auto regression (VAR) model to test the impact of a change on money supply and stock market price. Hen (2003) used a VAR model for Granger causality test and found the relationship between Money Supply (M1) and stock price.

The major purpose of this study is using macroeconomic variables (e.g. exchange rate, interest rate, money in circulation etc.) to forecast stock market crash before financial crisis. The specific objectives of the study are as follows:

(1) To determinant calculate, if any, the causal relationship between macroeconomic variables and stock market index in Hong Kong
(2) To explore whether such causality, if any, is unidirectional or bidirectional
(3) To find out time lap of such causality between macroeconomic variables and stock market index in Hong Kong
(4) To forecast stock market crash using macroeconomic variables in the future.

2. Literature Review

2.1 Stock Market Crash

Financial crisis is always accompanied with stock market collapse. In the 1929 Great Crash, the frantic equity collapse lasted for 8 days, with approximate 70.8 million shares were traded (Klein, 2001). On October 19, 1987, Dow Jones Industrial Average fell 508 points, a drop of 22.6% in one day (Shiller, 1987).Stock market crash refers to a sudden dramatic decline of stock prices within a stock market, resulting in a tremendous decline of monetary value of stock share (Stock market crash, n.d.). Such huge decline of share price is triggered by investors' panic selling. Psychological factor like positive feedback loop aggravates such panic when selling of some market participants drive more investors to sell.

Galbraith (1961) stated that in general, equity market crash would occur under the following conditions: exorbitant economic optimism and soaring equity prices; P/E ratio exceeds long-term averages; extensively using margin and leverage by investors.

Previous researches find that macroeconomic indicators like foreign exchange reserves and exchange rate have an impact on stock prices (Bhattacharya & Mukherjee, 2003)[1]. Chen *et al.* (1986) is one of the earliest attempts. Fama (1981) examined interest rate, expected inflation rate and unexpected inflation rate to stock returns. By applying the macroeconomic variables, stock market performance can be evaluated and examined (Fama, 1990). Akella and Chen (1990) found that stock market had a positive relationship to long-term government security, but a negative one with short-term government security. Fung *et al.* (2014a) use conditional consumption and market volatilities to explain abnormal return differences[2]. An occasional unidirectional causal relationship was found between interest rate and stock price in Hong Kong (Mok, 1993). For exchange rate, it would affect a company's foreign operation and profit and have an impact on stock price (Soenen & Hennigar, 1988).Aggarwal (1981) found that exchange rate and stock price were positively correlated. On the other hand, Soenen and Hennigar (1988) perceived a negative relationship between US stock price and US dollar. In addition, exchange rate and stock price could even have a mixed relationship (Soenen & Aggarwal, 1989).

However, under weak form Efficient Market Hypothesis (EMH), stock price should follow random walk and reflects all the past information up to current time point (Fama, 1970). Accordingly, if macro sectors really affect stock prices, stock market should have instantaneously reflected and incorporated all the available information. Bhattacharya & Mukherjee (2003) found that there was no causal relationship between macroeconomic variables (e.g. exchange rate, interest rate and trade balance) and BSE Sensitive Index. Even though Aggarwal(1981) found there was a positive relationship between exchange rate and stock, the causality was coincident instead of predictive.

2.2 Exchange Rate

In order to test the causal relationship between exchange rate and stock prices, Bahmani-Oskooee and Sohrabian (1992) applied Granger causality test and cointegration to explain the phenomenon. Mohammad, Hussain, and Ali (2009) observed a causal relationship between exchange rate and Karachi stock market (KSE). Real exchange rate of RMB and Hong Kong market index are positive correlated (Lee, 2012).

Aggarwal (1981) observed a coincidental causal relationship between US dollar and stock prices. This result was consolidated by Abdalla and Murinde (1997), who examined the data in India, Korea and Pakistan.

However, the causal relationship between exchange rate and stock prices could be vague and ambiguous. As Mok (1993) found a bidirectional relationship exchange rates and stock returns in Hong Kong. In addition, Smith (1992) found that stock returns Granger cause the exchange rate in Germany, Japan and the United States. Besides, stock prices lead the exchange rates in Philippines, Abdalla and Murinde market (Abdalla and Murinde, 1997).

2.3 HIBOR

We usually assume that there should be a negative relationship between interest rate and the stock price, in that a rise in the interest rate decreases the present value of future dividend income, which would depress stock prices.

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[1] Value-at Risk (VaR) is another popular measure of financial crisis in finance (Tardivo, 2002; Fung and Wan, 2013).

[2] For an application of developing country, see Fung *et al.* (2014b).

According to the theory of Mishkin (2000), the rise in interest rate resulted from tightening monetary, makes the bonds more attractive relative to stocks thereby caused the stock prices to fall. Therefore, an unusually high interest rate may cause the stock market to fall. One refers to die low interest rates that prevailed in the years prior to the global crisis (Sánchez, 2011). Rigobon and Sack (2002) concluded that increases in the short-term interest rate have a negative impact on stock prices, with the largest effect on the NASDAQ index. Using a Granger-Sims test on weekly data for the period 1980 to 1986, causality was found to run mostly from the interest rates to stock price changes but not vice versa in the United States (Hashemzadeh and Taylor, 1988).

Wong, Khan, & Du (2005) found that stock markets in Singapore moved in tandem with interest rate and money supply before the Asian Crisis of 1997, but this pattern was not observed after crisis. Ajayi, Friedman and Mehdian (1999) found unilateral Granger causality from interest rate to stock market and he concluded that the interest rate has significantly positive influence on stock price. Hamao (1988) found that the expected inflation rate may cause a change in the risk premium and in the term structure of interest rate. Sun and Ma (2003) found that when the effective way PBoC uses to adjust the stock market by monetary policy is the interest rate for its important influence on stock price. We want to know the actual relationship between interest rate and financial crisis in this paper.

2.4 Money Supply

The money supply reflects the different degrees of liquidity different types of money have. The narrowest measure, M1, is restricted to the most liquid forms of money; it consists of currency in the hands of the public; traveler's checks; demand deposits, and other deposits against which checks can be written. M2 includes M1, plus savings accounts, time deposits of under $100,000, and balances in retail money market mutual funds (Federal Reserve Bank of New York, 2008). How does the money supply influence the stock price? Tantatape and Komain (2007) concluded that money supply had a positive impact on the stock market index while the industrial production index, the exchange rate and oil prices had a negative impact. Mishkin (2000) argued that when a tight monetary policy narrow the money supply, the people will find that they have less money to spend both in the household consumption and in the stock market. As the result, the stock price falls for less demand.

Dhakal, Kandil, and Sharma (1993) used a vector auto regression (VAR) model to test the impact of a change in the money supply on a change in the stock market index under a money market equilibrium condition. They found that there is a significant relationship between these two variables in the United States. Chen (2003) used a VAR model for Granger causality test and found a positive relationship between Money Supply (M1) and stock price in China. Abdullah and Haywarth (1993) also concluded that a difference in the market index was influenced by the interest rate and by the flotation of the money supply. However, Fung and Lie (1990) summarized that the result of the stock market index to the correlation between domestic production and money supply was not that strong in Korea. This means, investors did not perceive a change in economic conditions could affect stock prices.

2.5 Treasury Bill Rate

Treasury bill is a short-term debt obligation backed by the U.S. government with a maturity of no more than one year. Treasury bill rate is defined as the annual yield rate to the investors. Many researches have been conducted to measure the interaction between the monetary policies and stock price index. Rigobon and Sack (2004) used Vector error correction model (VECM) to employ daily data on 3-month Treasury bill rate and daily return on the S&P 500 index from March 1985 to December 1999. He found that monetary policy responds significantly to stock market movements with a 5% increase (decrease) in the S&P 500 index increasing the probability of a tightening (easing) by approximately a half.

However, when Johansen cointegation technique and VECM was applied by SOHAIL and ZAKIR (2010) to test the long run and short run relationships of five macroeconomic variables on General Index, they used monthly data (from November 1991 to June 2008) to analyze General Index and concluded that money supply and three month treasury bills rate affected stock prices negatively in the long run. The variance of the model indicated that consumer price index and money supply showed greater forecast error than real effective exchange rate, industrial production index, and three month treasury bills rate for General Index. Thus, the influence of treasury bills rate is quite significant in his research.

However, the significance of the result may depend on their choice of sample period and estimation model. Data in different period and different locations may have different result. Iglesias and Haughton (2011) use monthly and annual data for Barbados, and annual data for Jamaica and T&T.

Their results show that in Barbados with monthly (and annual) data, a stock price shock that increases stock prices by 1% results in an increase in the Treasury bill rate of 30 (and 190) basis points. For Jamaica, a stock price shock that increases stock prices by 1% results in an increase in the Treasury bill rate of 400 basis points. Likewise for T&T a shock leading to a 1% increase in real stock prices causes the Treasury bill to increase by 330 basis points. Kuwornu's (2012) study shows that, in the short run, Treasury Bill Rate significantly influences the stock returns, with and an elasticity of 0.005, implying that a 1% rise in the Treasury bill rate will lead to a 0.005% rise in the stock returns. In the long run, the effect of Treasury bill rate is highly inelastic with elasticity of 0.003.

3. Methodology and Data Source

3.1 Measurement and Sample Design

The present study applies time serious of daily data for the period from 2007 to 2010, when subprime mortgage occurs, for Hong Kong market of the following variables: Hang Seng Index (HSI), real exchange rate, interest rate and money supply. The data is extracted from Yahoo Finance and Hong Kong Monetary Authority.

Data of exchange rate is quoted as US dollar per Hong Kong dollar (USD per HKD). Real exchange rate would be adjusted by inflation for US and Hong Kong. Interest rate would be used daily Hong Kong Interbank Offered Rate (HIBOR) as a measurement. M1 data would be applied to estimate money supply.

3.2 Methodology

This study is based on Granger causality test and Vector Autoregressive model (VAR).The first step is to apply unit root test to test the stationary of the (weekly) macroeconomic time series and Hong Kong stock market index (HSI) during 2008. Since many time series variables of order 1 are non-stationary (Engle and Granger, 1987), unite root test would be applied to avoid the spurious regression. Augmented Dickey-Fuller (ADF) will be conducted on this purpose.

Second step is to determine the causality between macroeconomic variables and stock market index using Granger causality test. The test is based on the following equation:

$$Y_t = \beta_0 + \sum_{k=1}^{M} \beta_k Y_{t-k} + \sum_{l=1}^{N} \alpha_l X_{t-l} + u_t$$

$$X_t = \gamma_0 + \sum_{k=1}^{M} \gamma_k Y_{t-k} + \sum_{l=1}^{N} \theta_l Y_{t-l} + v_t$$

where X and Y are the variables to be tested, u_t and v_t are white noise and uncorrelated with each other.If α_l is significant, we say X Granger causes Y and there is a causal relationship between X and Y.

If there is a causal relationship between the macroeconomic variable and HSI, the VAR model could be written as:

$$HSI_t = \alpha_1 + \sum_{i=1}^{i} \beta_{1i} HSI_{t-i} + \sum_{i=1}^{i} \gamma_{1i} Int_{t-i} + \sum_{i=1}^{i} \delta_{1i} EX_{t-i} + \sum_{i=1}^{i} \tau_{1i} MS_{t-i} + \sum_{i=1}^{i} \Delta_{1i} TB_{t-i} + \varepsilon_1$$

$$Int_t = \alpha_2 + \sum_{i=1}^{i} \beta_{2i} Int_{t-i} + \sum_{i=1}^{i} \gamma_{2i} EX_{t-i} + \sum_{i=1}^{i} \delta_{2i} MS_{t-i} + \sum_{i=1}^{i} \tau_{2i} HSI_{t-i} + \sum_{i=1}^{i} \Delta_{1i} TB_{t-i} + \varepsilon_2$$

$$EX_t = \alpha_3 + \sum_{i=1}^{i} \beta_{3i} EX_{t-i} + \sum_{i=1}^{i} \gamma_{3i} MS_{t-i} + \sum_{i=1}^{i} \delta_{3i} HSI_{t-i} + \sum_{i=1}^{i} \tau_{3i} Int_{t-i} + \sum_{i=1}^{i} \Delta_{1i} TB_{t-i} + \varepsilon_3$$

$$MS_t = \alpha_4 + \sum_{i=1}^{i} \beta_{4i} MS_{t-i} + \sum_{i=1}^{i} \gamma_{4i} HSI_{t-i} + \sum_{i=1}^{i} \delta_{4i} EX_{t-i} + \sum_{i=1}^{i} \tau_{4i} MS_{t-i} + \sum_{i=1}^{i} \Delta_{1i} TB_{t-i} + \varepsilon_4$$

$$TB_t = \alpha_4 + \sum_{i=1}^{i} \beta_{5i} MS_{t-i} + \sum_{i=1}^{i} \gamma_{5i} HSI_{t-i} + \sum_{i=1}^{i} \delta_{5i} EX_{t-i} + \sum_{i=1}^{i} \tau_{5i} MS_{t-i} + \sum_{i=1}^{i} \Delta_{1i} TB_{t-i} + \varepsilon_5$$

Where HSI is the Hang Seng Index;
Int is the HIBOR rate;
EX is the real exchange rate between Hong Kong and United State
MS is the money supply;
ε_i is the white noise disturbance term.

Considering one period time lag, the model could be casted in matrix form as:

$$\begin{pmatrix} HSI_t \\ Int_t \\ EX_t \\ MS_t \\ TB_t \end{pmatrix} = \begin{pmatrix} \alpha_1 \\ \alpha_2 \\ \alpha_3 \\ \alpha_4 \\ \alpha_5 \end{pmatrix} + \begin{pmatrix} \beta_{11} & \gamma_{11} & \delta_{11} & \tau_{11} & \Delta_{11} \\ \Delta_{21} & \beta_{21} & \gamma_{21} & \delta_{21} & \tau_{21} \\ \tau_{31} & \Delta_{31} & \beta_{31} & \gamma_{31} & \delta_{31} \\ \delta_{41} & \tau_{41} & \Delta_{41} & \beta_{41} & \gamma_{41} \\ \gamma_{51} & \delta_{51} & \tau_{51} & \Delta_{51} & \beta_{51} \end{pmatrix} \begin{pmatrix} HSI_{t-1} \\ Int_{t-1} \\ EX_{t-1} \\ MS_{t-1} \\ TB_{t-1} \end{pmatrix} + \begin{pmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \varepsilon_3 \\ \varepsilon_4 \\ \varepsilon_5 \end{pmatrix}, E \begin{pmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \varepsilon_3 \\ \varepsilon_4 \\ \varepsilon_5 \end{pmatrix} = 0$$

In order to find out the optimal time lag, Hsiao's Granger Causality test was found to provide more accurate results in determining lag length (Bhattacharya and Mukherjee, 2003). Hsiao's optimum lag length first conducts series of autoregression of one time lag. In each of the following autoregression, adding one more time lag on the dependent variable then calculate the FPE score base on the following equation:

$$FPE(m) = \sigma^2 \frac{n+m+1}{n-m-1}$$

where FPE is the final prediction error;

m is the time lag;

n is the sample size;

σ^2 is the estimated error variance that is computed for each order m.

The optimal time lag is the one with the smallest FPE score.

4. Data Analysis

4.1 Testing Stationary for the Variables and the System

For time series forecasting, the model or the whole should be stationary, otherwise spurious regression would occur (Brooks, 2008). In order to test the stationary for each variable, we conduct unit root test for each individual variable.

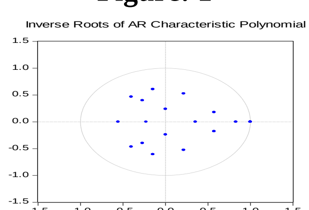
Table 1: Unit Root Test of Variables.

variable	t-Statistic	Prob.
HSI	-1.26358	0.6357
Exchange rate	-1.50892	0.5178
M1 money supply	-1.568049	0.4882
T-Bill rate	-0.473361	0.8930
HIBOR	-1.316787	0.6112

*MacKinnon (1996) one-sided p-values.

From Table 1, we can find that all the p values are greater than 0.05, meaning that none of the variables are stationary with I(0).For the Vector Autoregressive (VAR) model, the stationary of the system is by the inverse of root. We found that is one root in the system of equation lying outside the unit circle as shown in Figure 1 - evidence of non-stationary.

Figure: 1



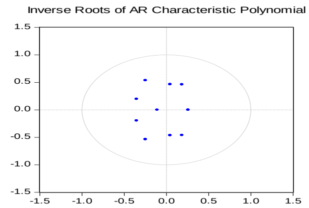
We proceed to transform the non-stationary variables into stationary ones by taking the first difference of each variable, and the unit test result is followed:

Table2: Unit Root Test of First-Differenced Series

variable	t-Statistic	Prob.
HSI	-12.00350	0.0000
Exchange rate	-13.12176	0.0000
M1 money supply	-13.70736	0.0000
T-Bill rate	-4.270625	0.0007
HIBOR	-15.95633	0.0000

From the Table 2, we can see that all the p values are less than 5%, therefore, all the variables are stationary under 1st difference. Thus, they are I(1) stationary.

Figure: 2



From the Figure 2, we can see all the inverse roots are less than one and within the unit cycle, which means the variables are stationary this time.

4.2 Choosing Optimal Lag for the VAR

In order to find the optimal lag for the VAR criteria, the following test is conducted:

Table 3: Choosing Optimal Lag by Various Criteria.

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-3004.927	NA	154.9922	19.23276	19.29260	19.25667
1	-2652.354	691.6296	19.11125	17.13964	17.49870*	17.28313
2	-2586.972	126.1674*	14.76663*	16.88161*	17.53989	17.14468*
3	-2569.597	32.97316	15.50860	16.93033	17.88783	17.31297
4	-2562.689	12.89026	17.41894	17.04593	18.30265	17.54815
5	-2547.423	27.99498	18.55368	17.10813	18.66407	17.72992
6	-2537.615	17.67394	20.47241	17.20521	19.06035	17.94657
7	-2527.672	17.59754	22.58188	17.30142	19.45579	18.16236
8	-2506.658	36.52380	23.22134	17.32689	19.78047	18.30740
9	-2495.000	19.88823	25.36774	17.41214	20.16494	18.51223
10	-2481.292	22.94881	27.37323	17.48430	20.53632	18.70396
* indicates lag order selected by the criterion						
LR: sequential modified LR test statistic (each test at 5% level)						
FPE: Final prediction error						
AIC: Akaike information criterion						
SC: Schwarz information criterion						
HQ: Hannan-Quinn information criterion						

From the Table 3, the smaller the test score, the better the model stimulates. Four among five criteria choose two lags for the VAR model, while SC chooses one lag. In short, we choose two lags for the VAR model.

4.3 Estimation of VAR Model:

Table 4: Vector Autoregressive Model

	EX_GROWTH	HIBOR_GROWTH	HSI_GROWTH	M1_GROWTH	T_BILL_GROWTH
EX_GROWTH(-1)	-0.066811	81.61253	-0.017711	-12.04302	12.71428
	(0.05613)	(13.9757)	(0.03375)	(2.84432)	(9.60025)
	[-1.19021]	[5.83962]	[-0.52476]	[-4.23406]	[1.32437]
EX_GROWTH(-2)	-0.068399	52.14878	-0.020679	-4.207844	10.87742
	(0.05872)	(14.6183)	(0.03530)	(2.97511)	(10.0417)
	[-1.16492]	[3.56736]	[-0.58576]	[-1.41435]	[1.08323]
HIBOR_GROWTH(-1)	-2.65E-05	-0.228423	7.38E-05	-0.016494	0.076592
	(0.00023)	(0.05664)	(0.00014)	(0.01153)	(0.03891)
	[-0.11667]	[-4.03310]	[0.53969]	[-1.43090]	[1.96867]
HIBOR_GROWTH(-2)	-0.000455	-0.016620	0.000259	-0.024097	-0.038537
	(0.00022)	(0.05404)	(0.00013)	(0.01100)	(0.03712)
	[-2.09545]	[-0.30757]	[1.98153]	[-2.19110]	[-1.03816]
HSI_GROWTH(-1)	0.169328	46.69014	0.019048	11.63362	30.70668
	(0.09511)	(23.6785)	(0.05718)	(4.81903)	(16.2653)
	[1.78042]	[1.97184]	[0.33311]	[2.41410]	[1.88786]
HSI_GROWTH(-2)	-0.077398	35.47803	-0.012109	6.180107	31.47114
	(0.09693)	(24.1338)	(0.05828)	(4.91170)	(16.5781)
	[-0.79845]	[1.47005]	[-0.20776]	[1.25824]	[1.89835]
M1_GROWTH(-1)	0.001387	-0.005404	0.000375	-0.521038	0.078334
	(0.00107)	(0.26598)	(0.00064)	(0.05413)	(0.18271)
	[1.29874]	[-0.02032]	[0.58321]	[-9.62526]	[0.42873]
M1_GROWTH(-2)	0.002322	-0.119017	0.000270	-0.334904	-0.077759
	(0.00105)	(0.26178)	(0.00063)	(0.05328)	(0.17982)
	[2.20848]	[-0.45465]	[0.42636]	[-6.28613]	[-0.43242]
T_BILL_GROWTH(-1)	0.000654	0.156508	-0.000125	-0.006406	0.204821
	(0.00032)	(0.07981)	(0.00019)	(0.01624)	(0.05482)
	[2.03984]	[1.96105]	[-0.64661]	[-0.39441]	[3.73608]
T_BILL_GROWTH(-2)	-0.000170	0.034779	0.000153	0.005399	-0.247831
	(0.00032)	(0.07964)	(0.00019)	(0.01621)	(0.05470)
	[-0.53261]	[0.43672]	[0.79415]	[0.33314]	[-4.53039]
C	-0.006423	-1.752235	0.009530	1.620969	-1.995903
	(0.00757)	(1.88559)	(0.00455)	(0.38375)	(1.29526)
	[-0.84803]	[-0.92928]	[2.09283]	[4.22398]	[-1.54093]

Table 4 reports the VAR results. To further test whether the model has prediction power, we conduct the Granger Casualty test to test whether independent variables could Granger cause dependent variables.

Table 5: VAR Granger Causality/Block Exogeneity Wald Tests

Dependent variable: HSI_GROWTH			
Excluded	Chi-sq	df	Prob.
EX_GROWTH	0.595257	2	0.7426
HIBOR_GROWTH	3.956332	2	0.1383
M1_GROWTH	0.387232	2	0.8240
T_BILL_GROWTH	0.913954	2	0.6332
All	6.063579	8	0.6401

From the Table 5, it is shown that none of the independent variables can Grange cause dependent variables. Therefore, the growth rate VAR model has little prediction power.

4.5 Cointegration and Vector Error Correction Model (VECM)

VAR may ignore long-term relationship between variables. We estimate the cointegration model in this section. Even though each individual variable is not stationary, their linear combination (cointegration vector) could be stationary. Such process is called cointegration. In order to be cointegrated, each variable must be t^{th} stationary, named I(t). From the previous part, we know that all the variables are followed I(1). Table 6 reports the Johansen Cointegration Test results.

Table 6: Johansen Cointegration Test results

Unrestricted Cointegration Rank Test (Trace)					
Hypothesized		Trace	0.05		
No. of CE(s)	Eigenvalue	Statistic	Critical Value	Prob.**	
None *	0.112702	81.98913	69.81889	0.0039	
At most 1	0.063538	43.60558	47.85613	0.1185	
At most 2	0.033760	22.53307	29.79707	0.2698	
At most 3	0.030758	11.50894	15.49471	0.1820	
At most 4	0.004602	1.480655	3.841466	0.2237	
Trace test indicates 1 cointegratingeqn(s) at the 0.05 level					
* denotes rejection of the hypothesis at the 0.05 level					
**MacKinnon-Haug-Michelis (1999) p-values					
Unrestricted Cointegration Rank Test (Maximum Eigenvalue)					
Hypothesized		Max-Eigen	0.05		
No. of CE(s)	Eigenvalue	Statistic	Critical Value	Prob.**	
None *	0.112702	38.38355	33.87687	0.0135	
At most 1	0.063538	21.07252	27.58434	0.2719	
At most 2	0.033760	11.02413	21.13162	0.6449	
At most 3	0.030758	10.02828	14.26460	0.2101	
At most 4	0.004602	1.480655	3.841466	0.2237	
Max-eigenvalue test indicates 1 cointegratingeqn(s) at the 0.05 level					
* denotes rejection of the hypothesis at the 0.05 level					
**MacKinnon-Haug-Michelis (1999) p-values					

The second line "At most 1" represents H_0: only one cointegration equation versus H_1: more than 1 cointegration equation. From the tables above, both Trace and Maximum Eigenvalue method indicates 1cointegration equation at the 5% level.

5. Results

5.1 Output of VAR Model.

We can write Table 4 in matrix form and generate the impulse response functions.

$$\begin{pmatrix} \mathrm{EXGROWTH_t} \\ \mathrm{HIBORGROWTH_t} \\ \mathrm{HSIGROWTH_t} \\ \mathrm{M1GROWTH_t} \\ \mathrm{TBILLGROWTH_t} \end{pmatrix} = \begin{pmatrix} -0.006423 \\ -1.752235 \\ 0.009530 \\ 1.620969 \\ -1.995903 \end{pmatrix} + \begin{pmatrix} -0.066811 & -2.65E-05 & 0.169328 & 0.001387 & 0.000654 \\ 81.61253 & -0.228423 & 46.69014 & -0.005404 & 0.156508 \\ -0.017711 & 7.38E-05 & 0.019048 & 0.000375 & -0.000125 \\ -12.04302 & -0.016494 & 11.63362 & -0.521038 & -0.006406 \\ 12.71428 & 0.076592 & 30.70668 & 0.078334 & 0.204821 \end{pmatrix} \begin{pmatrix} EX_{t-1} \\ HIB_{t-1} \\ HSI_{t-1} \\ M1S_{t-1} \\ TBILL_{t-1} \end{pmatrix}$$

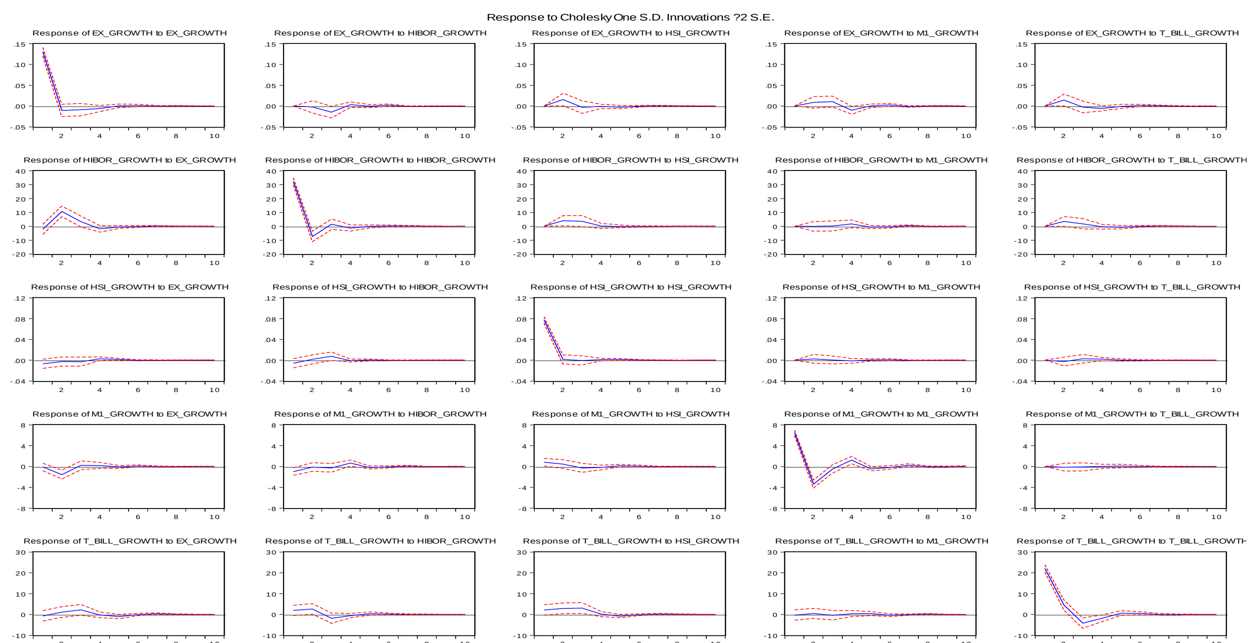
$$+ \begin{pmatrix} -0.068399 & -0.000455 & -0.077398 & 0.002322 & -0.000170 \\ 52.14878 & -0.016620 & 35.47803 & -0.119017 & 0.034779 \\ -0.020679 & 0.000259 & -0.012109 & 0.000270 & 0.000153 \\ -4.207844 & -0.024097 & 6.180107 & -0.334904 & 0.005399 \\ 10.87742 & -0.038537 & 31.47114 & -0.077759 & -0.247831 \end{pmatrix} \begin{pmatrix} EX_{t-2} \\ HIB_{t-2} \\ HSI_{t-2} \\ M1S_{t-2} \\ TBILL_{t-2} \end{pmatrix} + \begin{pmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \varepsilon_3 \\ \varepsilon_4 \\ \varepsilon_5 \end{pmatrix}, E \begin{pmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \varepsilon_3 \\ \varepsilon_4 \\ \varepsilon_5 \end{pmatrix} = 0$$

An impulse response function traces the effect of a one-time shock to one of the innovations on current and future values of the endogenous variables. We report the impulse response functions in Figure 3.

The graphs in the third row show how many percentages of HSI changes given 1% change of each individual variable: EX_GROWTH, HIBOR_GROWTH, HSI_GROWTH, M1_GROWTH, and T-BILL_GROWTH.

The response of 1% change in EX_GROWTH will cause 0.7% negative change of HSI_GROWTH in the first month, 0.3% negative change in the second and third month. In a similar way, 1% change of HIBOR_GROWTH has a 0.6 negative change on HSI_GROWTH in the first month, 0.2% positive effect in the second month and 0.8% positive effect positive effect in the third month. For a change to M1_GROWTH, it does not cause effect in the first and third month, only 0.2%positive effect in the second month, which is negligible. The response to 1% change in BILL_GROWTH, it has not effect in the first month and 0.3% negative in the second month and 0.3% positive change in the third month, which is inconspicuous either.

Figure 3: Impulse Response Functions



From all above, VAR model seems not suitable to predict the Hang SengIndex, maybe we can find their long term relationship through Vector Error Correction Model.

5.2 Vector Error Correction Model

From the output of the cointegration equation (Table 7), we can estimate the long run equilibrium relation of these variables

HIS (-1) = 3008335 +30692.22 T_BILL(-1) -26369.80 HIBOR(-1) +0.025690 M1(-1) -389203.4 EX(-1)

Table 7: Cointegration Equation

Cointegrating Eq:	**CointEq1**
HSI(-1)	1.000000
T_BILL(-1)	-30692.22
	(5337.05)
	[-5.75078]
HIBOR(-1)	26369.80
	(4287.24)
	[6.15076]
M1(-1)	-0.025690
	(0.01536)
	[-1.67259]
EX(-1)	389203.4
	(144433.)
	[2.69469]
C	-3008335.

Table 8: shows the result of error correction part representing the short run relations.

Table 8: Vector Error Correction Model

Error Correction:	D(HSI)	D(T_BILL)	D(HIBOR)	D(M1)	D(EX)
CointEq1	-0.002990	-7.42E-07	-9.21E-06	0.074102	-6.34E-08
	(0.00256)	(4.4E-07)	(1.9E-06)	(0.08276)	(2.5E-08)
	[-1.16971]	[-1.69379]	[-4.86786]	[0.89537]	[-2.48619]
D(HSI(-1))	0.039978	1.86E-05	1.49E-05	9.896160	1.03E-06
	(0.05785)	(9.9E-06)	(4.3E-05)	(1.87291)	(5.8E-07)
	[0.69102]	[1.87830]	[0.34930]	[5.28383]	[1.79364]
D(HSI(-2))	0.085918	9.82E-06	-3.89E-05	4.172573	-6.59E-08
	(0.05989)	(1.0E-05)	(4.4E-05)	(1.93898)	(6.0E-07)
	[1.43451]	[0.95673]	[-0.87803]	[2.15194]	[-0.11037]
D(T_BILL(-1))	-649.8804	0.412470	0.531426	9087.801	0.003685
	(348.943)	(0.05980)	(0.25813)	(11296.5)	(0.00348)
	[-1.86242]	[6.89716]	[2.05874]	[0.80448]	[1.05915]
D(T_BILL(-2))	227.1683	0.028021	0.294853	-10951.25	-0.007382
	(348.622)	(0.05975)	(0.25789)	(11286.1)	(0.00348)
	[0.65162]	[0.46900]	[1.14331]	[-0.97033]	[-2.12373]
D(HIBOR(-1))	140.3007	0.016008	-0.248909	943.2625	0.000993
	(84.2865)	(0.01445)	(0.06235)	(2728.66)	(0.00084)
	[1.66457]	[1.10822]	[-3.99204]	[0.34569]	[1.18152]
D(HIBOR(-2))	160.2261	0.009606	-0.109774	1216.894	0.000144
	(76.6692)	(0.01314)	(0.05672)	(2482.06)	(0.00076)
	[2.08984]	[0.73108]	[-1.93549]	[0.49028]	[0.18788]
D(M1(-1))	0.001087	1.86E-07	4.49E-07	-0.501108	2.52E-08
	(0.00169)	(2.9E-07)	(1.3E-06)	(0.05472)	(1.7E-08)
	[0.64294]	[0.64346]	[0.35928]	[-9.15835]	[1.49393]
D(M1(-2))	-0.001771	1.90E-07	-8.03E-07	-0.297252	3.69E-08
	(0.00161)	(2.8E-07)	(1.2E-06)	(0.05209)	(1.6E-08)
	[-1.10085]	[0.68726]	[-0.67421]	[-5.70631]	[2.30159]
D(EX(-1))	-5432.111	-0.155774	6.964299	-822703.1	-0.072393
	(5703.09)	(0.97741)	(4.21888)	(184629.)	(0.05686)
	[-0.95249]	[-0.15937]	[1.65074]	[-4.45597]	[-1.27318]
D(EX(-2))	-6197.103	0.241103	6.654647	-254320.7	-0.041610
	(5749.02)	(0.98528)	(4.25286)	(186116.)	(0.05732)
	[-1.07794]	[0.24470]	[1.56475]	[-1.36646]	[-0.72595]
C	52.95282	-0.012990	0.003945	7073.685	-0.000549
	(58.1029)	(0.00996)	(0.04298)	(1881.00)	(0.00058)
	[0.91136]	[-1.30447]	[0.09178]	[3.76060]	[-0.94756]
R-squared	0.051529	0.254412	0.249043	0.311506	0.082039
Adj. R-squared	0.017765	0.227870	0.222310	0.286996	0.049361
Akaike AIC	16.71438	-0.628840	2.295999	23.66907	-6.317480
Schwarz SC	16.85537	-0.487851	2.436987	23.81006	-6.176492

We can write the equitation that：

$\Delta(HSI)=52.95282+0.039978*\Delta(HSI(-1))+ 0.085918*\Delta(HSI(-2))+ -649.8804*\Delta(T\_BILL(-1))+ 227.1683*\Delta(T\_BILL(-2))+ 140.3007*\Delta(HIBOR(-1))+ 160.2261*\Delta(HIBOR(-2))+ 0.001087*\Delta(M1(-1))+ -0.001771*\Delta(M1(-2))+ -5432.111*\Delta(EX(-1))+ -6197.103*\Delta(EX(-2))$

We can find that the coefficients of both the first and second difference of $\Delta HIBOR$are positive, to interpret this, we build a logical assumption between the refugee capital, or called hot money, and the stock price. When the hot refugee capital flow to Hong Kong, the demand for Hong Kong Dollar (HKD) will increase, the reserve of HKD in bank will decrease, which will push up the interest rate between banks, represented by HIBOR here. After a period of time lag, according to the VAR Lag Order Selection Criteria test we have done, it is one or two month, the inflow money investing in the market will push up the stock price in Hong Kong, represented by HSI here. As a result, there is a positive signal between HIBOR and HSI.

5.3 Granger Causality test of VECM

Table 9: Granger Causality Test of VECM

Dependent variable: D(HSI)			
Excluded	Chi-sq	df	Prob.
D(T_BILL)	3.468965	2	0.1765
D(HIBOR)	5.141919	2	0.0765
D(M1)	2.532966	2	0.2818
D(EX)	1.944632	2	0.3782
All	14.60115	8	0.0674

From Table 9: it is clear that $\Delta HIBOR$ can granger cause ΔHSI under 10% significant level.

Table 10: checks the dual granger causality：

Table 10: Dual Grange Causality Test

Dependent variable: D(HIBOR)

Excluded	Chi-sq	df	Prob.
D(HSI)	0.910352	2	0.6343
D(T_BILL)	6.794113	2	0.0335
D(M1)	0.849350	2	0.6540
D(EX)	4.030322	2	0.1333
All	12.88306	8	0.1159

As the result shows, ΔHSI cannot granger cause $HIBOR$ in reverse.

From Table 10, we can find that although the 1st differential T_BILL (-1) has a significant coefficient to 1st differential HSI in the equation, however they do not have granger causal relationship. The 1st differential HIBOR (-1), and 1st differential HIBOR(-2) is significant to the short run 1st differential HSI and granger cause it.

5.4 Comparison for Different Financial Crisis

For this part, we divide the period into three parts according to the financial crisis period for comparison. Date of each period begins at the last month of last crisis and ends at the last month of this financial crisis. Period 2 is from September 1998 to April 2003 and Period 3 is from May 2003 to February 2009

Table 11a: Granger Causality Test of Period 2

Dependent variable: D(HIS)			
Excluded	Chi-sq	df	Prob.
D(HIBOR)	0.244166	2	0.8851
D(T_BILL)	0.972285	2	0.6150
D(EX)	5.387111	2	0.0676
D(M1)	0.704771	2	0.7030
All	9.500666	8	0.3018

Table 11b: Granger Causality Test of Period 3

Dependent variable: D(HIS)			
Excluded	Chi-sq	df	Prob.
D(HIBOR)	5.211338	2	0.0739
D(T_BILL)	14.37282	2	0.0008
D(EX)	0.161621	2	0.9224
D(M1)	0.826386	2	0.6615
All	26.54364	8	0.0008

Table 11a and 11b show the Granger Causality Test for VECM model for different periods.

From the tables, we can find that for the first two financial crisis, five independent variables have little power to granger causal HSI. However, for the last period, the 2008 subprime crisis, there is a causal relationship between these five variables. Specially, US T bill rate is the most significant variable to Granger cause HSI. Under 10% critical value, HIBOR rate can also Granger causes HSI.

Table 12a and 12b show the impulse response functions of Period 2 and Period 3, respectively.

Table 12a: Impulse Response Functions of Period 2

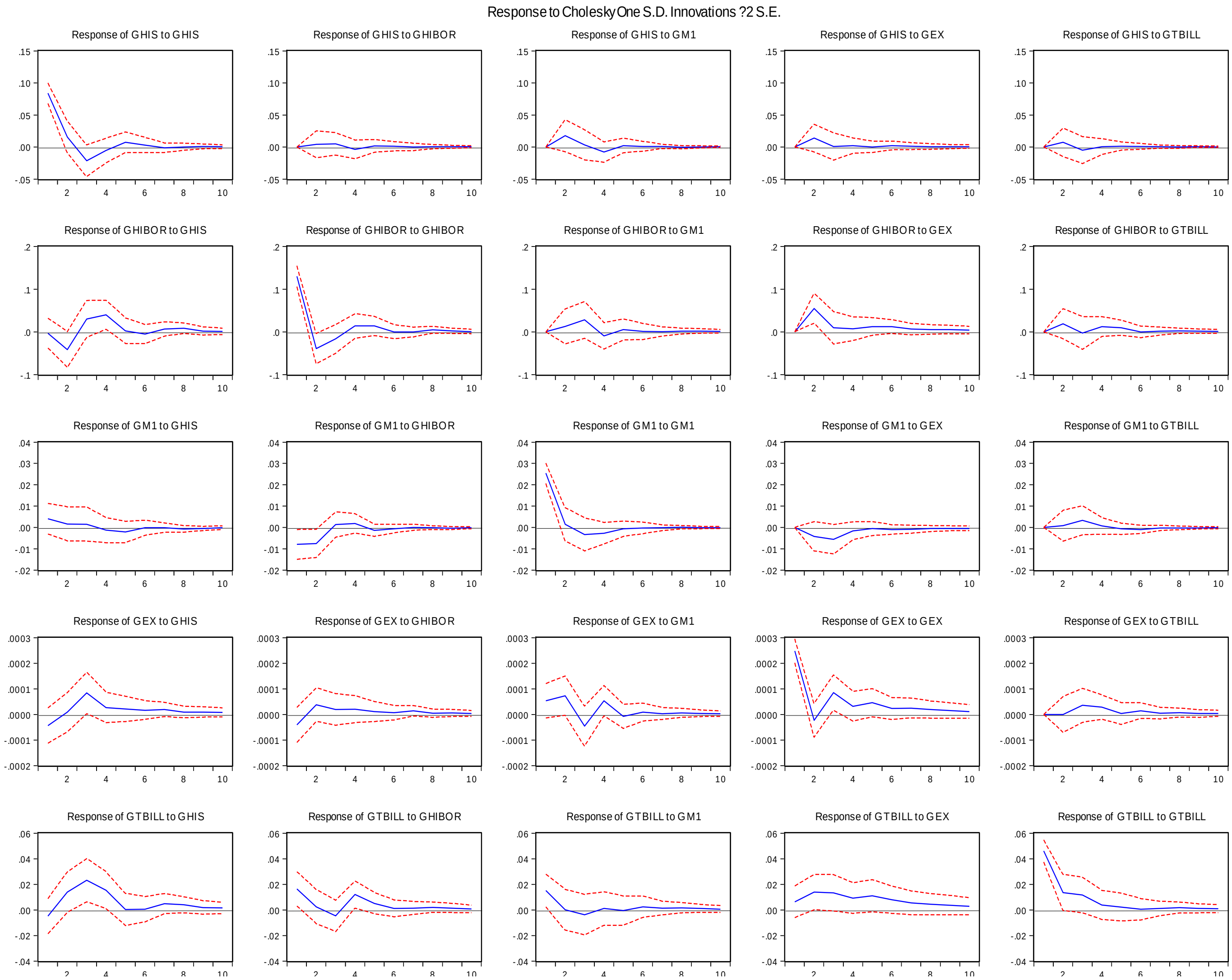
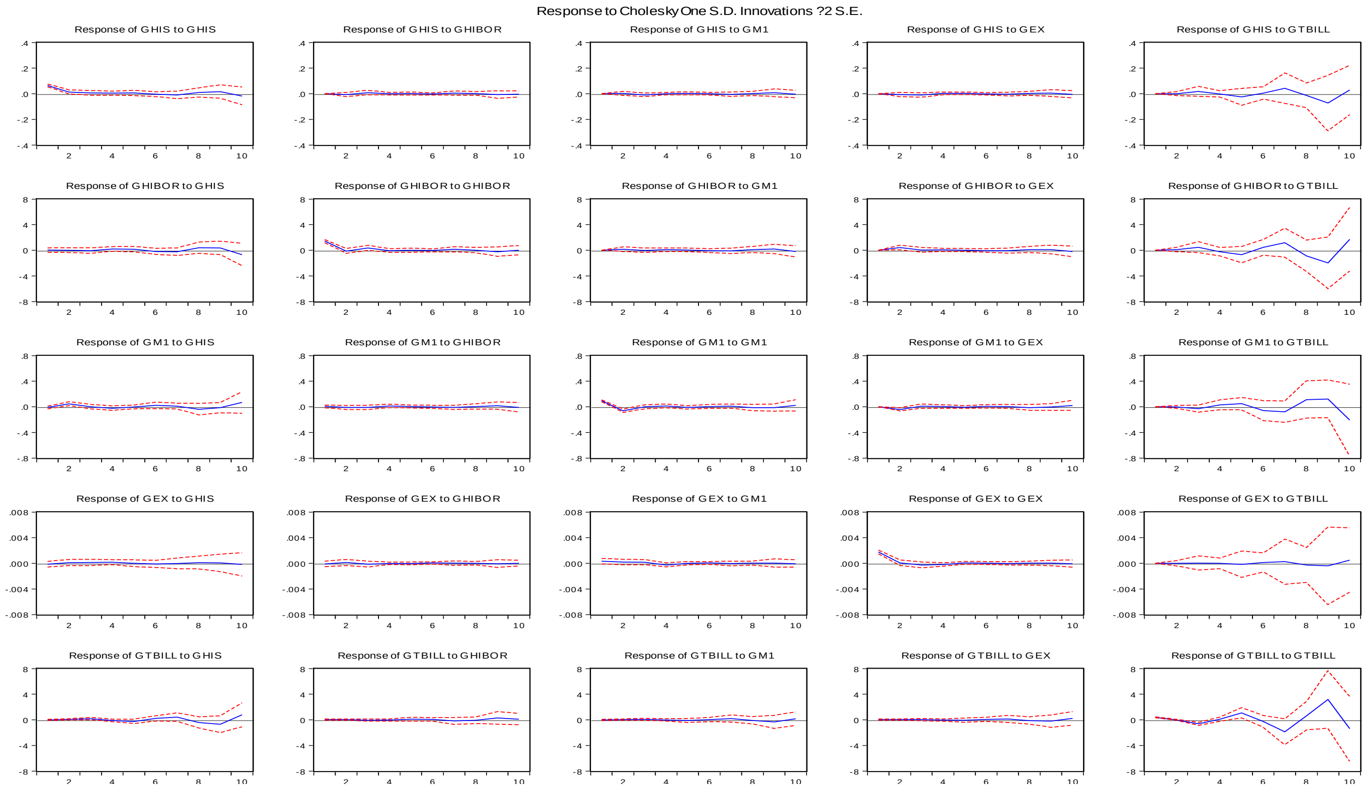


Table 12b: Impulse Response Functions of Period 3



Taking the growth rate of each independent variable, we transform the nonstationary time series variables into stationary ones.

For the stationary variables, we utilize VAR model and the impulse response function to conduct the analysis that how many percentage of HSI changes given 1% change of each individual variable. For period 1, 1% change in HIBOR causes 1.1% change in HSI and 1% change in T bill rate causes -1.8% changes in the HSI. For period 2, 1% change in M1 results in 1.8% change in HSI and 1% change in exchange rate results in 1.4% changes in HSI. For period 3, impulse response for each variable is not very obvious.

Conclusion may be driven from the test above that the Granger cause and impulse response vary from period to period.

6. Conclusion

The major objective of this study is using macroeconomic variables: exchange rate, HIBOR, money in circulation, and T-Bill rate to forecast stock market crash before financial crisis. We find out Vector Autoregressive model is not suitable to our data sample, from 1987 to 2013. When we change to Vector Error Correction Model, to find out its long-term relationship, the result shows the relationship between macroeconomic variables and stock market index in Hong Kong as following:

$$HSI(-1)= 3008335 +30692.22\ T\_BILL(-1) -26369.80\ HIBOR(-1) +0.025690\ M1(-1) -389203.4\ EX(-1)$$

From the error correction test, we find their short run relation:

$$\Delta(HSI)=52.95282+0.039978*\Delta(HSI(-1))+ 0.085918*\Delta(HSI(-2))+ -649.8804*\Delta(T\_BILL(-1))+ 227.1683*\Delta(T\_BILL(-2))+ 140.3007*\Delta(HIBOR(-1))+ 160.2261*\Delta(HIBOR(-2))+ 0.001087*\Delta(M1(-1))+ -0.001771*\Delta(M1(-2))+ -5432.111*\Delta(EX(-1))+ -6197.103*\Delta(EX(-2))$$

Among these variables, $\Delta(HIBOR(-1))$ and $\Delta(HIBOR(-2))$ are significant and granger cause $\Delta(HSI)$, and the causality is unidirectional. Using VAR Lag Order Selection Criteria, we find out the most significant time lap of such causality between macroeconomic variables and stock market index in Hong Kong is two month. In conclusion, we can use one or two month forward HIBOR to forecast stock market crash in the future base overall sample between 1987 and 2013. However, base on the further study in three separate periods, forecast result may vary from period to period.

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